

```

1 . set seed 1010101

2 . set matsize 11000

3 .
4 .
5 . *****
6 .
7 . *   This script requires pre-installation of spost2 by J. Scott Long for fit
   > stat command
8 . *   It also requires installation of title2.ado, title3.ado
9 . *
10 . *       for the fitstat command to function
11 . *****
12 .
13 . global User   "Robert Alan Yaffee"

14 . * 17 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 .
47 . ***-----
    > -----
48 .
49 . * Part 2 Nottingham subscales
50 . * 1: hp2work
51 . * 2: hp2hmcare
52 . * 3: hp2probsoc
53 . * 4: hp2pbfhm

```



```

67 .
68 . cd /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests/h1
    > pt2
    /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2

69 . use chwide16june2012, clear
    (Zero for missing on all icdx)

70 . cd /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests/h1
    > pt2
    /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2

71 .
72 .
73 . di "{hline}"


---



74 . di "{hline}"


---



75 . title2 "Chunk 1 Hyp 1: radiation dose and Nottingham Health profile subscales
    > "


---


title2: Chunk 1 Hyp 1: radiation dose and Nottingham Health profile subscales
Date and time: 17 Jun 2012 10:03:05
Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2
Stata data file: chwide16june2012.dta
> has 2373 variables and 703 observations

Chunk 1 Hyp 1: radiation dose and Nottingham Health profile subscales


---



76 .
77 .
78 . // there is substantial intercorrelation among the items warranting a
79 . // multivariate regression model

```

```

80 . cap dummies educ
81 . cap order educ1-educ8, after(educ)
82 .
83 . * These variables are substantially correlated
84 . 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

```

85 .
86 . cap gen havmilsq = havmil^2

87 .
88 . cap rename Havmil havmil

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

95 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

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

97 .
98 . *-----
    > ----
99 . * Hypothesis 1 Part 2 Wave 2 tests male and female
100 . * endogeneous Nottingham pt 2 subscales: HP2work HP2hmcare HP2probsoc HP2pbfh
    > m ///
    > *
    HP2sxlife HP2inthob HP2vacatn
101 . * structure of models
102 . * 1. general models on all Pt 2 subscales with all potential confounders
103 . * 2. trimmed models on all Pt 2 subscales with from all potential confoun
    > ders
104 . * 3. from trimmed models examination of possible moderator variables
105 . * 4. from trimmed models examination of possible mediator variables
106 . * 5. Summary analysis and model evaluation of final models only
107 . * program is divided into 8 chunks one a general model and 1 for each
108 . * endogenous variable
109 . *-----
    > ----
110 . * Chunk 1 General models for all part 2 of Nottingham Health Profile

```

```

111 .
112 .
113 . forvalues j=2/2 {
      2. des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
>    bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      3. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)


```

118 . title4 "Full main model for `var' for wave= `j' "
      8. di _skip(4)
      9. title4 "chunk 2 H1 test:Gender= `k' model Wave = `j' for `e(depvar)' "
     10. di _skip(4)
     11. title4 "Full Nottingham Part 2 `var' subscale models" "wave `j' for gende
> r==`k'"
     12.
119 .      xi: logit `var' age i.educ occlw`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', difficult iterate(500) nolog
     13.          estat class
     14.          estat gof
     15.          fitstat
     16. }
     17. }
     18. }

```

Full main model for HP2work for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for hp2work

Full Nottingham Part 2 HP2work subscale models

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

note: _Ieduc_4 != 0 predicts failure perfectly

 _Ieduc_4 dropped and 12 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: sepaw2 != 0 predicts failure perfectly

 sepaw2 dropped and 6 obs not used

note: _Ieduc_6 omitted because of collinearity

note: bf15 omitted because of collinearity

Logistic regression

Number of obs = 308

LR chi2(42) = 109.94

Prob > chi2 = 0.0000

Log likelihood = -106.34944

Pseudo R2 = 0.3408

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	-.0001692	.02372	-0.01	0.994	-.0466595	.0463212
_Ieduc_2	.9181743	1.013818	0.91	0.365	-1.068872	2.90522
_Ieduc_3	-.0025163	.4641718	-0.01	0.996	-.9122764	.9072438
_Ieduc_4	0	(omitted)				
_Ieduc_5	.7217689	.6474494	1.11	0.265	-.5472086	1.990746
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-2.033983	2.039062	-1.00	0.319	-6.030472	1.962506
occ2w2	-1.10022	2.055368	-0.54	0.592	-5.128666	2.928227
occ3w2	-1.57744	2.098973	-0.75	0.452	-5.691352	2.536471
occ4w2	-.7778101	2.07516	-0.37	0.708	-4.845048	3.289428
occ5w2	-.1994034	2.080334	-0.10	0.924	-4.276783	3.877976
occ6w2	.5724938	2.922442	0.20	0.845	-5.155386	6.300374
occ7w2	1.385601	2.162361	0.64	0.522	-2.852549	5.623751
occ8w2	-2.621626	2.185931	-1.20	0.230	-6.905973	1.66272
marrw21	14.46418	1445.103	0.01	0.992	-2817.886	2846.815
marrw22	16.06999	1445.104	0.01	0.991	-2816.281	2848.421
marrw23	13.00974	1445.103	0.01	0.993	-2819.341	2845.36
marrw25	15.20349	1445.106	0.01	0.992	-2817.151	2847.558
marrw26	11.50222	1445.104	0.01	0.994	-2820.85	2843.855
inc1w2	-1.510512	2.275504	-0.66	0.507	-5.970418	2.949394
inc2w2	-.2432446	2.068579	-0.12	0.906	-4.297585	3.811096
inc3w2	1.229267	2.059579	0.60	0.551	-2.807434	5.265968
inc4w2	.0340459	2.516571	0.01	0.989	-4.898343	4.966435
radhlw2	-.0036868	.0074975	-0.49	0.623	-.0183817	.0110081
havmil	.0013907	.0046392	0.30	0.764	-.0077019	.0104833
avgcumdosew2	.0423433	.0838158	0.51	0.613	-.1219326	.2066192
bf1	-.0106479	.0111601	-0.95	0.340	-.0325212	.0112255
bf4	-.1742962	.0530725	-3.28	0.001	-.2783165	-.070276
bf6	.0126216	.0084824	1.49	0.137	-.0040036	.0292468
bf7	.1335412	.0775552	1.72	0.085	-.0184641	.2855465
bf14	.000083	.0000711	1.17	0.243	-.0000564	.0002224
bf15	0	(omitted)				
bf40	.4649883	.132263	3.52	0.000	.2057576	.724219
deaw2	.0562824	.3164534	0.18	0.859	-.5639548	.6765196
dvcew2	.8659697	2.382497	0.36	0.716	-3.803639	5.535578
sepaw2	0	(omitted)				
accdw2	.5552759	.4404199	1.26	0.207	-.3079312	1.418483
movew2	.6056941	.4689768	1.29	0.197	-.3134835	1.524872
illw2	-.0279332	.3103275	-0.09	0.928	-.6361639	.5802975

shfamw2	.0059196	.0069893	0.85	0.397	-.0077792	.0196183
shhlw2	.0168978	.0087333	1.93	0.053	-.000219	.0340147
shjobw2	-.0044984	.0081883	-0.55	0.583	-.0205472	.0115504
shrelaw2	-.0237032	.0083387	-2.84	0.004	-.0400468	-.0073596
suprtw2	-.0017568	.0059642	-0.29	0.768	-.0134464	.0099328
suchrw2	.003038	.005693	0.53	0.594	-.00812	.014196
havmilsq	-1.38e-06	6.35e-06	-0.22	0.828	-.0000138	.0000111
_cons	-14.33587	1445.105	-0.01	0.992	-2846.689	2818.017

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	35	13	48
-	32	228	260
Total	67	241	308

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	52.24%
Specificity	$\Pr(- \sim D)$	94.61%
Positive predictive value	$\Pr(D +)$	72.92%
Negative predictive value	$\Pr(\sim D -)$	87.69%
False + rate for true ~D	$\Pr(+ \sim D)$	5.39%
False - rate for true D	$\Pr(- D)$	47.76%
False + rate for classified +	$\Pr(\sim D +)$	27.08%
False - rate for classified -	$\Pr(D -)$	12.31%
Correctly classified		85.39%

Logistic model for HP2work, goodness-of-fit test

number of observations =	308
number of covariate patterns =	308
Pearson chi2(265) =	283.15
Prob > chi2 =	0.2119

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

Log-Lik Intercept Only:	-161.320	Log-Lik Full Model:	-106.349
D(259):	212.699	LR(42):	109.942
		Prob > LR:	0.000
McFadden's R2:	0.341	McFadden's Adj R2:	0.037
Maximum Likelihood R2:	0.300	Cragg & Uhler's R2:	0.462
McKelvey and Zavoina's R2:	0.625	Efron's R2:	0.371
Variance of y*:	8.782	Variance of error:	3.290
Count R2:	0.854	Adj Count R2:	0.328
AIC:	1.009	AIC*n:	310.699
BIC:	-1271.397	BIC':	130.723

Full main model for HP2work for wave= 2

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

Full Nottingham Part 2 HP2work subscale models

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

note: sepaw2 != 0 predicts failure perfectly

 sepaw2 dropped and 8 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw26 omitted because of collinearity

note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	354
	LR chi2(44)	=	104.77
	Prob > chi2	=	0.0000
Log likelihood = -150.43517	Pseudo R2	=	0.2583

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0369848	.0167931	2.20	0.028	.0040708	.0698987
_Ieduc_2	-13.278	655.1046	-0.02	0.984	-1297.259	1270.703
_Ieduc_3	-13.76722	655.1045	-0.02	0.983	-1297.749	1270.214
_Ieduc_4	-12.56241	655.1048	-0.02	0.985	-1296.544	1271.419
_Ieduc_5	-14.16942	655.1047	-0.02	0.983	-1298.151	1269.812
_Ieduc_6	-13.46911	655.1045	-0.02	0.984	-1297.45	1270.512
_Ieduc_7	-13.6852	655.1071	-0.02	0.983	-1297.672	1270.301
_Ieduc_8	0	(omitted)				
occ1w2	-1.431885	1.490412	-0.96	0.337	-4.353039	1.48927
occ2w2	-1.067234	1.511451	-0.71	0.480	-4.029624	1.895156
occ3w2	-.6094536	1.500907	-0.41	0.685	-3.551177	2.33227

occ4w2	-.7773088	1.581059	-0.49	0.623	-3.876128	2.321511
occ5w2	-1.784723	1.846534	-0.97	0.334	-5.403863	1.834417
occ6w2	-1.506062	1.711274	-0.88	0.379	-4.860097	1.847973
occ7w2	-.374184	1.45347	-0.26	0.797	-3.222934	2.474566
occ8w2	-.0539674	1.70334	-0.03	0.975	-3.392452	3.284517
marrw21	-.7235313	1.007239	-0.72	0.473	-2.697684	1.250621
marrw22	-.7861921	1.258786	-0.62	0.532	-3.253367	1.680983
marrw23	-.156903	.704389	-0.22	0.824	-1.53748	1.223674
marrw25	-.4149071	1.124423	-0.37	0.712	-2.618736	1.788922
marrw26	0	(omitted)				
inclw2	-.3011188	1.506651	-0.20	0.842	-3.2541	2.651862
inc2w2	.2687204	1.456307	0.18	0.854	-2.585589	3.12303
inc3w2	1.036312	1.469535	0.71	0.481	-1.843923	3.916546
inc4w2	-.1137536	1.952911	-0.06	0.954	-3.941389	3.713882
radhlw2	.0092993	.0058818	1.58	0.114	-.0022288	.0208273
havmil	-.0020615	.0026074	-0.79	0.429	-.0071719	.0030489
avgcumdosew2	.0807064	.0968033	0.83	0.404	-.1090246	.2704374
bf1	-.004698	.0078862	-0.60	0.551	-.0201547	.0107586
bf4	-.1182241	.0355711	-3.32	0.001	-.1879422	-.0485059
bf6	.001791	.0066699	0.27	0.788	-.0112818	.0148637
bf7	-.0450377	.0737224	-0.61	0.541	-.1895309	.0994556
bf14	-.0001102	.0000711	-1.55	0.121	-.0002496	.0000292
bf15	0	(omitted)				
bf40	.0952395	.072172	1.32	0.187	-.046215	.236694
deaw2	.164384	.1960927	0.84	0.402	-.2199507	.5487186
dvcew2	-.2821707	1.333785	-0.21	0.832	-2.89634	2.331999
sepaw2	0	(omitted)				
accdw2	.6916732	.4937096	1.40	0.161	-.2759799	1.659326
movew2	-.1373653	.5055449	-0.27	0.786	-1.128215	.8534845
illw2	.1336732	.1739566	0.77	0.442	-.2072754	.4746219
shfamw2	-.0053174	.0059668	-0.89	0.373	-.0170122	.0063773
shhlw2	.0054362	.0062416	0.87	0.384	-.0067971	.0176695
shjobw2	-.0006072	.0057431	-0.11	0.916	-.0118635	.0106491
shrelaw2	-.0064495	.0065479	-0.98	0.325	-.0192832	.0063841
suprtw2	-.0047857	.0047915	-1.00	0.318	-.0141769	.0046055
suchrw2	.009761	.0053132	1.84	0.066	-.0006528	.0201747
havmilsq	2.04e-07	1.76e-06	0.12	0.908	-3.25e-06	3.65e-06
_cons	11.57916	655.1066	0.02	0.986	-1272.406	1295.565

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	44	21	65
-	48	241	289
Total	92	262	354

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	47.83%
Specificity	$\Pr(- \sim D)$	91.98%
Positive predictive value	$\Pr(D +)$	67.69%
Negative predictive value	$\Pr(\sim D -)$	83.39%
False + rate for true ~D	$\Pr(+ \sim D)$	8.02%
False - rate for true D	$\Pr(- D)$	52.17%
False + rate for classified +	$\Pr(\sim D +)$	32.31%
False - rate for classified -	$\Pr(D -)$	16.61%
Correctly classified		80.51%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      354
number of covariate patterns =    354
    Pearson chi2(309) =    452.09
        Prob > chi2 =      0.0000

```

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

Log-Lik Intercept Only:	-202.820	Log-Lik Full Model:	-150.435
D(305):	300.870	LR(44):	104.770
		Prob > LR:	0.000
McFadden's R2:	0.258	McFadden's Adj R2:	0.017
Maximum Likelihood R2:	0.256	Cragg & Uhler's R2:	0.376
McKelvey and Zavoina's R2:	0.477	Efron's R2:	0.297
Variance of y*:	6.291	Variance of error:	3.290
Count R2:	0.805	Adj Count R2:	0.250
AIC:	1.127	AIC*n:	398.870
BIC:	-1489.265	BIC':	153.479

Full main model for HP2hmcare for wave= 2

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

Full Nottingham Part 2 HP2hmcare subscale models

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

note: _Ieduc_4 != 0 predicts failure perfectly

 _Ieduc_4 dropped and 12 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ8w2 != 0 predicts failure perfectly

 occ8w2 dropped and 43 obs not used

note: sepaw2 != 0 predicts failure perfectly

 sepaw2 dropped and 6 obs not used

note: _Ieduc_7 omitted because of collinearity

note: bf15 omitted because of collinearity

Logistic regression

Number of obs = 269

LR chi2(42) = 109.76

Prob > chi2 = 0.0000

Pseudo R2 = 0.3609

Log likelihood = -97.204962

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0338165	.0226356	1.49	0.135	-.0105484	.0781815
_Ieduc_2	-4.276213	1.974151	-2.17	0.030	-8.145479	-.406947
_Ieduc_3	-2.496446	1.569642	-1.59	0.112	-5.572887	.579995
_Ieduc_4	0	(omitted)				
_Ieduc_5	-1.933257	1.595074	-1.21	0.226	-5.059545	1.193031
_Ieduc_6	-2.731404	1.5115	-1.81	0.071	-5.693888	.2310807
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	.447866	3.337423	0.13	0.893	-6.093362	6.989094
occ2w2	-.0398	3.356232	-0.01	0.991	-6.617893	6.538293
occ3w2	.5016738	3.37088	0.15	0.882	-6.105129	7.108476
occ4w2	.4812856	3.378935	0.14	0.887	-6.141306	7.103877
occ5w2	1.51252	3.404132	0.44	0.657	-5.159455	8.184496
occ6w2	2.9603	3.825064	0.77	0.439	-4.536687	10.45729
occ7w2	.5681102	3.446364	0.16	0.869	-6.186638	7.322859
occ8w2	0	(omitted)				
marrw21	-1.554879	1.682488	-0.92	0.355	-4.852495	1.742737
marrw22	-3.80953	2.028746	-1.88	0.060	-7.785799	.1667393

marrw23	-3.665421	1.71283	-2.14	0.032	-7.022506	-.3083347
marrw25	-1.481731	4.126728	-0.36	0.720	-9.56997	6.606508
marrw26	-2.880741	2.479902	-1.16	0.245	-7.741261	1.979778
inclw2	2.844486	3.430733	0.83	0.407	-3.879627	9.568599
inc2w2	2.655327	3.349177	0.79	0.428	-3.908939	9.219593
inc3w2	3.052721	3.355091	0.91	0.363	-3.523137	9.628579
inc4w2	1.171678	3.639724	0.32	0.748	-5.96205	8.305406
radhlw2	-.0026842	.0077227	-0.35	0.728	-.0178205	.0124521
havmil	.002871	.0081498	0.35	0.725	-.0131023	.0188444
avgcumdosew2	-.0220473	.0954292	-0.23	0.817	-.2090852	.1649906
bf1	-.0176257	.0110209	-1.60	0.110	-.0392262	.0039748
bf4	-.3209329	.0601062	-5.34	0.000	-.4387388	-.203127
bf6	.0142094	.0096047	1.48	0.139	-.0046155	.0330342
bf7	.1041093	.0843677	1.23	0.217	-.0612484	.269467
bf14	5.78e-06	.0000736	0.08	0.937	-.0001386	.0001501
bf15	0	(omitted)				
bf40	.3500268	.1396049	2.51	0.012	.0764063	.6236473
deaw2	.0522034	.3200036	0.16	0.870	-.5749921	.6793989
dvcew2	-.370905	3.78656	-0.10	0.922	-7.792426	7.050615
sepaw2	0	(omitted)				
accdw2	.1929199	.4604851	0.42	0.675	-.7096143	1.095454
movew2	.2586331	.5214207	0.50	0.620	-.7633328	1.280599
illw2	-.1291222	.3453441	-0.37	0.708	-.8059842	.5477398
shfamw2	-.0123461	.0080757	-1.53	0.126	-.0281741	.0034819
shhlw2	-.0067088	.0095447	-0.70	0.482	-.0254161	.0119985
shjobw2	-.0001525	.009703	-0.02	0.987	-.0191701	.018865
shrelaw2	.0044873	.0074837	0.60	0.549	-.0101805	.0191551
suprtw2	.0138227	.0067373	2.05	0.040	.0006178	.0270276
suchrw2	-.0024443	.0059474	-0.41	0.681	-.0141011	.0092124
havmilsq	-7.11e-06	.0000151	-0.47	0.639	-.0000368	.0000226
_cons	1.915103	3.160353	0.61	0.545	-4.279075	8.109282

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	38	14	52
-	30	187	217
Total	68	201	269

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

Sensitivity	$\Pr(+ D)$	55.88%
Specificity	$\Pr(- \sim D)$	93.03%
Positive predictive value	$\Pr(D +)$	73.08%
Negative predictive value	$\Pr(\sim D -)$	86.18%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	6.97%
False - rate for true D	$\Pr(- D)$	44.12%
False + rate for classified +	$\Pr(\sim D +)$	26.92%
False - rate for classified -	$\Pr(D -)$	13.82%

Correctly classified	83.64%
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Logistic model for HP2hmcare, goodness-of-fit test

number of observations =	269
number of covariate patterns =	269
Pearson $\chi^2(226)$ =	228.79
Prob > χ^2 =	0.4356

Measures of Fit for **logit** of HP2hmcare

Log-Lik Intercept Only:	-152.087	Log-Lik Full Model:	-97.205
D(220):	194.410	LR(42):	109.763
		Prob > LR:	0.000
McFadden's R2:	0.361	McFadden's Adj R2:	0.039
Maximum Likelihood R2:	0.335	Cragg & Uhler's R2:	0.495
McKelvey and Zavoina's R2:	0.599	Efron's R2:	0.381
Variance of y^* :	8.208	Variance of error:	3.290
Count R2:	0.836	Adj Count R2:	0.353
AIC:	1.087	AIC*n:	292.410
BIC:	-1036.427	BIC':	125.215

Full main model for HP2hmcare for wave= 2

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

Full Nottingham Part 2 HP2hmcare subscale models

i.educ	_Ieduc_1-8	(naturally coded; _Ieduc_1 omitted)
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note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression

Number of obs = 362
LR chi2(45) = 176.34
Prob > chi2 = 0.0000
Pseudo R2 = 0.3790

Log likelihood = -144.48759

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0738943	.0179039	4.13	0.000	.0388033	.1089852
_Ieduc_2	-14.47538	1273.657	-0.01	0.991	-2510.798	2481.847
_Ieduc_3	-15.05547	1273.657	-0.01	0.991	-2511.378	2481.267
_Ieduc_4	-13.48341	1273.657	-0.01	0.992	-2509.806	2482.839
_Ieduc_5	-14.88762	1273.657	-0.01	0.991	-2511.21	2481.435
_Ieduc_6	-15.58826	1273.657	-0.01	0.990	-2511.911	2480.734
_Ieduc_7	-13.81171	1273.659	-0.01	0.991	-2510.137	2482.513
_Ieduc_8	0	(omitted)				
occ1w2	-2.359905	1.509597	-1.56	0.118	-5.318661	.5988504
occ2w2	-2.373759	1.546944	-1.53	0.125	-5.405713	.6581945
occ3w2	-1.535666	1.553674	-0.99	0.323	-4.58081	1.509479
occ4w2	-2.972204	1.655316	-1.80	0.073	-6.216564	.2721556
occ5w2	-4.352791	1.883178	-2.31	0.021	-8.043752	-.6618289
occ6w2	-5.059677	2.021732	-2.50	0.012	-9.022199	-1.097155
occ7w2	-1.364295	1.545156	-0.88	0.377	-4.392746	1.664156
occ8w2	-.5789576	1.792303	-0.32	0.747	-4.091808	2.933892
marrw21	-.0690078	1.129464	-0.06	0.951	-2.282717	2.144702
marrw22	.7043443	1.44356	0.49	0.626	-2.124982	3.533671
marrw23	2.097285	.8281102	2.53	0.011	.4742186	3.720351
marrw25	.9609574	1.20757	0.80	0.426	-1.405836	3.327751
marrw26	0	(omitted)				
inc1w2	2.105274	1.594442	1.32	0.187	-1.019775	5.230323
inc2w2	3.407471	1.542788	2.21	0.027	.3836621	6.43128
inc3w2	2.870172	1.549672	1.85	0.064	-.1671285	5.907473
inc4w2	3.606463	1.894634	1.90	0.057	-.1069505	7.319876
radhlw2	-.0068123	.0061828	-1.10	0.271	-.0189302	.0053057
havmil	.0011484	.0030211	0.38	0.704	-.0047728	.0070696
avgcumdosew2	-.2667926	.1232968	-2.16	0.030	-.5084499	-.0251353
bf1	-.0183931	.0079003	-2.33	0.020	-.0338774	-.0029088
bf4	-.2337773	.0416245	-5.62	0.000	-.3153598	-.1521948
bf6	.0040038	.0067939	0.59	0.556	-.009312	.0173196
bf7	-.126659	.0709704	-1.78	0.074	-.2657584	.0124404
bf14	-.0000228	.0000659	-0.35	0.729	-.0001521	.0001064
bf15	0	(omitted)				
bf40	.0786288	.0758899	1.04	0.300	-.0701127	.2273704
deaw2	.6463714	.2506264	2.58	0.010	.1551526	1.13759
dvcew2	1.46465	1.066188	1.37	0.170	-.6250398	3.554339

sepaw2	-1.747364	1.628008	-1.07	0.283	-4.938201	1.443472
accdw2	-.6760904	.5387942	-1.25	0.210	-1.732108	.3799268
movev2	-.5261615	.493185	-1.07	0.286	-1.492786	.4404633
illw2	-.1619986	.1844507	-0.88	0.380	-.5235154	.1995182
shfamw2	-.0039886	.0060041	-0.66	0.506	-.0157565	.0077793
shhlw2	-.0091905	.0062486	-1.47	0.141	-.0214375	.0030565
shjobw2	.0003458	.0057176	0.06	0.952	-.0108605	.011552
shrelaw2	-.0091776	.006756	-1.36	0.174	-.0224192	.0040639
suprtw2	-.0077623	.0046946	-1.65	0.098	-.0169635	.0014389
suchrw2	.0040413	.0050755	0.80	0.426	-.0059065	.013989
havmilsq	-1.23e-06	2.83e-06	-0.44	0.664	-6.79e-06	4.32e-06
_cons	12.31935	1273.659	0.01	0.992	-2484.005	2508.644

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	85	27	112
-	39	211	250
Total	124	238	362

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

Sensitivity	$\Pr(+ D)$	68.55%
Specificity	$\Pr(- \sim D)$	88.66%
Positive predictive value	$\Pr(D +)$	75.89%
Negative predictive value	$\Pr(\sim D -)$	84.40%
False + rate for true ~D	$\Pr(+ \sim D)$	11.34%
False - rate for true D	$\Pr(- D)$	31.45%
False + rate for classified +	$\Pr(\sim D +)$	24.11%
False - rate for classified -	$\Pr(D -)$	15.60%
Correctly classified		81.77%

Logistic model for HP2hmcare, goodness-of-fit test

number of observations =	362
number of covariate patterns =	362
Pearson chi2(316) =	339.77
Prob > chi2 =	0.1713

Measures of Fit for **logit** of **HP2hmcare**

Log-Lik Intercept Only:	-232.660	Log-Lik Full Model:	-144.488
D(313):	288.975	LR(45):	176.345
		Prob > LR:	0.000
McFadden's R2:	0.379	McFadden's Adj R2:	0.168
Maximum Likelihood R2:	0.386	Cragg & Uhler's R2:	0.533
McKelvey and Zavoina's R2:	0.660	Efron's R2:	0.429
Variance of y*:	9.672	Variance of error:	3.290
Count R2:	0.818	Adj Count R2:	0.468
AIC:	1.069	AIC*n:	386.975
BIC:	-1555.109	BIC':	88.779

Full main model for HP2probsoc for wave= 2

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

Full Nottingham Part 2 HP2probsoc subscale models

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

note: _Ieduc_4 != 0 predicts failure perfectly

 _Ieduc_4 dropped and 12 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ6w2 != 0 predicts failure perfectly

 occ6w2 dropped and 4 obs not used

note: occ7w2 != 0 predicts failure perfectly

 occ7w2 dropped and 14 obs not used

note: occ8w2 != 0 predicts failure perfectly

 occ8w2 dropped and 43 obs not used

note: marrw22 != 0 predicts failure perfectly

 marrw22 dropped and 7 obs not used

note: marrw25 != 0 predicts failure perfectly

 marrw25 dropped and 4 obs not used

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

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 3 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	228
	LR chi2(34)	=	103.91
	Prob > chi2	=	0.0000
Log likelihood = -52.36582	Pseudo R2	=	0.4980

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0906854	.0339814	2.67	0.008	.0240831	.1572876
_Ieduc_2	-.0346926	1.161856	-0.03	0.976	-2.311888	2.242503
_Ieduc_3	-.6886648	.7207042	-0.96	0.339	-2.101219	.7238895
_Ieduc_4	0	(omitted)				
_Ieduc_5	.9759744	1.063631	0.92	0.359	-1.108703	3.060652
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-.9172264	10.67202	-0.09	0.932	-21.83401	19.99955
occ2w2	-.7254984	10.66823	-0.07	0.946	-21.63485	20.18385
occ3w2	-.6714679	10.68886	-0.06	0.950	-21.62126	20.27832
occ4w2	-2.239171	10.70842	-0.21	0.834	-23.22728	18.74894
occ5w2	-.9195542	10.71455	-0.09	0.932	-21.91968	20.08057
occ6w2	0	(omitted)				
occ7w2	0	(omitted)				
occ8w2	0	(omitted)				
marrw21	11.0684	1379.375	0.01	0.994	-2692.457	2714.594
marrw22	0	(omitted)				
marrw23	8.945925	1379.375	0.01	0.995	-2694.579	2712.471
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inc1w2	.3641243	10.76623	0.03	0.973	-20.7373	21.46555
inc2w2	1.742499	10.67327	0.16	0.870	-19.17672	22.66172
inc3w2	3.371881	10.68463	0.32	0.752	-17.56961	24.31337
inc4w2	0	(omitted)				
radhlw2	.0085407	.0114129	0.75	0.454	-.0138281	.0309095

havmil	-.0006807	.0078287	-0.09	0.931	-.0160246	.0146632
avgcumdosew2	.099739	.0947343	1.05	0.292	-.0859367	.2854148
bf1	.0048596	.0179991	0.27	0.787	-.0304181	.0401372
bf4	-.3368708	.0845017	-3.99	0.000	-.5024911	-.1712504
bf6	.0294921	.0150976	1.95	0.051	-.0000987	.0590829
bf7	.2107792	.1280115	1.65	0.100	-.0401186	.4616771
bf14	-.0000508	.0001111	-0.46	0.648	-.0002685	.0001669
bf15	0	(omitted)				
bf40	.3587504	.202109	1.78	0.076	-.0373759	.7548768
deaw2	-.2425986	.5320938	-0.46	0.648	-1.285483	.8002861
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0583869	.772113	-0.08	0.940	-1.571701	1.454927
movew2	.534895	.8346364	0.64	0.522	-1.100962	2.170752
illw2	.3093012	.430894	0.72	0.473	-.5352355	1.153838
shfamw2	-.0138199	.0107438	-1.29	0.198	-.0348774	.0072375
shhlw2	-.0108054	.0127581	-0.85	0.397	-.0358108	.0141999
shjobw2	.024033	.0121387	1.98	0.048	.0002416	.0478244
shrelaw2	-.0263531	.0111814	-2.36	0.018	-.0482683	-.0044379
suprtw2	.0130386	.0099595	1.31	0.190	-.0064816	.0325589
suchrw2	.0121677	.0099924	1.22	0.223	-.007417	.0317524
havmilsq	4.68e-06	9.92e-06	0.47	0.637	-.0000148	.0000241
_cons	-18.63366	1379.378	-0.01	0.989	-2722.164	2684.897

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	27	4	31
-	12	185	197
Total	39	189	228

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

Sensitivity	$\Pr(+ D)$	69.23%
Specificity	$\Pr(- \sim D)$	97.88%
Positive predictive value	$\Pr(D +)$	87.10%
Negative predictive value	$\Pr(\sim D -)$	93.91%

False + rate for true ~D	$\Pr(+ \sim D)$	2.12%
False - rate for true D	$\Pr(- D)$	30.77%
False + rate for classified +	$\Pr(\sim D +)$	12.90%
False - rate for classified -	$\Pr(D -)$	6.09%

Correctly classified 92.98%

Logistic model for HP2probsoc, goodness-of-fit test

```
number of observations =      228
number of covariate patterns =    228
      Pearson chi2(193) =    730.19
      Prob > chi2 =      0.0000
```

Measures of Fit for logit of HP2probsoc

Log-Lik Intercept Only:	-104.322	Log-Lik Full Model:	-52.366
D(179):	104.732	LR(34):	103.912
		Prob > LR:	0.000
McFadden's R2:	0.498	McFadden's Adj R2:	0.028
Maximum Likelihood R2:	0.366	Cragg & Uhler's R2:	0.611
McKelvey and Zavoina's R2:	0.779	Efron's R2:	0.554
Variance of y*:	14.912	Variance of error:	3.290
Count R2:	0.930	Adj Count R2:	0.590
AIC:	0.889	AIC*n:	202.732
BIC:	-867.121	BIC':	80.686

Full main model for HP2probsoc for wave= 2

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

Full Nottingham Part 2 HP2probsoc subscale models

```
i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: occ6w2 != 0 predicts failure perfectly
      occ6w2 dropped and 9 obs not used
```

```
note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity
```

Logistic regression	Number of obs	=	353
	LR chi2(44)	=	173.44
	Prob > chi2	=	0.0000
Log likelihood = -93.198778	Pseudo R2	=	0.4820

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1045505	.025349	4.12	0.000	.0548673	.1542337
_Ieduc_2	-12.29812	1030.765	-0.01	0.990	-2032.56	2007.964
_Ieduc_3	-12.54704	1030.765	-0.01	0.990	-2032.809	2007.715
_Ieduc_4	-11.69817	1030.765	-0.01	0.991	-2031.96	2008.564
_Ieduc_5	-11.74738	1030.765	-0.01	0.991	-2032.009	2008.515
_Ieduc_6	-12.89754	1030.765	-0.01	0.990	-2033.159	2007.364
_Ieduc_7	-14.11644	1030.817	-0.01	0.989	-2034.481	2006.248
_Ieduc_8	0	(omitted)				
occ1w2	-1.104757	3.60974	-0.31	0.760	-8.179718	5.970203
occ2w2	-1.202019	3.652886	-0.33	0.742	-8.361544	5.957506
occ3w2	.0703933	3.628444	0.02	0.985	-7.041227	7.182014
occ4w2	-1.52192	3.712086	-0.41	0.682	-8.797475	5.753635
occ5w2	-2.24588	3.84541	-0.58	0.559	-9.782745	5.290985
occ6w2	0	(omitted)				
occ7w2	-.4840598	3.61697	-0.13	0.894	-7.573191	6.605072
occ8w2	2.167215	3.89814	0.56	0.578	-5.472999	9.807428
marrw21	-.4201784	1.629029	-0.26	0.796	-3.613016	2.772659
marrw22	1.086175	1.72569	0.63	0.529	-2.296115	4.468466
marrw23	.7750978	.9250885	0.84	0.402	-1.038042	2.588238
marrw25	.532399	1.287582	0.41	0.679	-1.991215	3.056013
marrw26	0	(omitted)				
inclw2	.0603839	3.624166	0.02	0.987	-7.042851	7.163619
inc2w2	.8383333	3.595272	0.23	0.816	-6.20827	7.884937
inc3w2	.536243	3.60018	0.15	0.882	-6.519981	7.592467
inc4w2	.2312155	3.842475	0.06	0.952	-7.299898	7.762329
radhlw2	.0147911	.0081819	1.81	0.071	-.0012451	.0308272
havmil	.0022418	.0072934	0.31	0.759	-.0120531	.0165366
avgcumdosew2	.4925829	.2091227	2.36	0.018	.0827098	.9024559
bf1	-.0161664	.0113442	-1.43	0.154	-.0384006	.0060677
bf4	-.2331375	.0505589	-4.61	0.000	-.332231	-.1340439
bf6	.0021871	.0094776	0.23	0.817	-.0163887	.0207629
bf7	-.0615381	.1064342	-0.58	0.563	-.2701454	.1470692
bf14	8.31e-06	.0000929	0.09	0.929	-.0001737	.0001903
bf15	0	(omitted)				
bf40	-.005756	.0971846	-0.06	0.953	-.1962344	.1847223
deaw2	-.0331928	.2378427	-0.14	0.889	-.499356	.4329704
dvcew2	1.930249	1.72923	1.12	0.264	-1.45898	5.319477
sepaw2	-1.211648	2.172861	-0.56	0.577	-5.470378	3.047082
accdw2	-.6584952	.7729357	-0.85	0.394	-2.173421	.8564309
movew2	-.3688091	.9599148	-0.38	0.701	-2.250208	1.512589
illw2	.0217672	.2703514	0.08	0.936	-.5081118	.5516462
shfamw2	-.0185511	.0084341	-2.20	0.028	-.0350816	-.0020206
shhlw2	.0005321	.0080879	0.07	0.948	-.0153199	.0163841
shjobw2	-.0024716	.0076938	-0.32	0.748	-.0175512	.0126079
shrelaw2	-.0052827	.0086543	-0.61	0.542	-.0222447	.0116794
suprtw2	.0005602	.0066528	0.08	0.933	-.012479	.0135994

suchrw2	-.0036935	.00718	-0.51	0.607	-.017766	.0103791
havmilsq	-8.46e-06	.0000154	-0.55	0.582	-.0000386	.0000217
_cons	6.917383	1030.768	0.01	0.995	-2013.35	2027.185

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	53	11	64
-	20	269	289
Total	73	280	353

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	72.60%
Specificity	$\Pr(- \sim D)$	96.07%
Positive predictive value	$\Pr(D +)$	82.81%
Negative predictive value	$\Pr(\sim D -)$	93.08%
False + rate for true ~D	$\Pr(+ \sim D)$	3.93%
False - rate for true D	$\Pr(- D)$	27.40%
False + rate for classified +	$\Pr(\sim D +)$	17.19%
False - rate for classified -	$\Pr(D -)$	6.92%
Correctly classified		91.22%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	353
number of covariate patterns =	353
Pearson chi2(308) =	419.21
Prob > chi2 =	0.0000

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-179.919	Log-Lik Full Model:	-93.199
D(304):	186.398	LR(44):	173.440
		Prob > LR:	0.000
McFadden's R2:	0.482	McFadden's Adj R2:	0.210
Maximum Likelihood R2:	0.388	Cragg & Uhler's R2:	0.607
McKelvey and Zavoina's R2:	0.892	Efron's R2:	0.528
Variance of y*:	30.526	Variance of error:	3.290
Count R2:	0.912	Adj Count R2:	0.575
AIC:	0.806	AIC*n:	284.398
BIC:	-1597.009	BIC':	84.685

Full main model for HP2pbfhm for wave= 2

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

Full Nottingham Part 2 HP2pbfhm subscale models

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 12 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ5w2 != 0 predicts failure perfectly

 occ5w2 dropped and 17 obs not used

note: occ6w2 != 0 predicts failure perfectly

 occ6w2 dropped and 4 obs not used

note: occ8w2 != 0 predicts failure perfectly

 occ8w2 dropped and 43 obs not used

note: marrw22 != 0 predicts failure perfectly

 marrw22 dropped and 7 obs not used

note: marrw25 != 0 predicts failure perfectly
marrw25 dropped and 4 obs not used

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

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

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 2 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	201
	LR chi2(32)	=	57.01
	Prob > chi2	=	0.0042
Log likelihood = -38.789787	Pseudo R2	=	0.4236

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0838902	.0451044	1.86	0.063	-.0045127	.1722932
_Ieduc_2	0	(omitted)				
_Ieduc_3	-1.068513	.9797271	-1.09	0.275	-2.988743	.851717
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.7464993	1.30613	-0.57	0.568	-3.306468	1.813469
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	1.365472	9.739165	0.14	0.888	-17.72294	20.45389
occ2w2	.1388058	9.737518	0.01	0.989	-18.94638	19.22399
occ3w2	1.99317	9.743118	0.20	0.838	-17.10299	21.08933
occ4w2	2.351827	9.813506	0.24	0.811	-16.88229	21.58595
occ5w2	0	(omitted)				
occ6w2	0	(omitted)				
occ7w2	.8526169	9.853293	0.09	0.931	-18.45948	20.16472
occ8w2	0	(omitted)				
marrw21	9.450183	1628.316	0.01	0.995	-3181.99	3200.891
marrw22	0	(omitted)				
marrw23	8.041239	1628.316	0.00	0.996	-3183.4	3199.482
marrw25	0	(omitted)				

marrw26	0	(omitted)				
inclw2	0	(omitted)				
inc2w2	-.2472615	9.778068	-0.03	0.980	-19.41192	18.9174
inc3w2	.4803685	9.779356	0.05	0.961	-18.68682	19.64755
inc4w2	0	(omitted)				
radhlw2	.0219991	.0174949	1.26	0.209	-.0122902	.0562884
havmil	-.0118024	.0110278	-1.07	0.285	-.0334164	.0098117
avgcumdosew2	-.108206	.7718766	-0.14	0.889	-1.621056	1.404644
bf1	-.0239769	.0247822	-0.97	0.333	-.0725492	.0245953
bf4	-.1619124	.088191	-1.84	0.066	-.3347635	.0109388
bf6	.0726065	.0265235	2.74	0.006	.0206214	.1245916
bf7	.5947613	.2273662	2.62	0.009	.1491317	1.040391
bf14	-.0000762	.0001284	-0.59	0.553	-.0003279	.0001756
bf15	0	(omitted)				
bf40	.1113503	.2734738	0.41	0.684	-.4246485	.6473491
deaw2	.5485131	.536457	1.02	0.307	-.5029234	1.59995
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	.185387	1.066161	0.17	0.862	-1.904251	2.275025
movew2	-.6539417	1.506102	-0.43	0.664	-3.605848	2.297965
illw2	1.606215	.6542566	2.46	0.014	.3238954	2.888534
shfamw2	-.0092438	.0132973	-0.70	0.487	-.0353061	.0168184
shhlw2	-.031707	.0186076	-1.70	0.088	-.0681771	.0047632
shjobw2	.0258976	.0158492	1.63	0.102	-.0051662	.0569614
shrelaw2	-.0153159	.0142321	-1.08	0.282	-.0432103	.0125785
suprtw2	-.0315277	.0143652	-2.19	0.028	-.059683	-.0033724
suchrw2	.0165746	.0112144	1.48	0.139	-.0054051	.0385544
havmilsq	.0000128	.0000121	1.06	0.291	-.000011	.0000367
_cons	-18.46331	1628.32	-0.01	0.991	-3209.912	3172.985

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	6	2	8
-	15	178	193
Total	21	180	201

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	28.57%
Specificity	$\Pr(- \sim D)$	98.89%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	92.23%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.11%
False - rate for true D	$\Pr(- D)$	71.43%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	7.77%

Correctly classified	91.54%
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Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	201
number of covariate patterns =	201
Pearson $\chi^2(168)$ =	94.58
Prob > χ^2 =	1.0000

Measures of Fit for **logit** of HP2pbfhm

Log-Lik Intercept Only:	-67.297	Log-Lik Full Model:	-38.790
D(152):	77.580	LR(32):	57.015
		Prob > LR:	0.004
McFadden's R2:	0.424	McFadden's Adj R2:	-0.305
Maximum Likelihood R2:	0.247	Cragg & Uhler's R2:	0.506
McKelvey and Zavoina's R2:	0.804	Efron's R2:	0.348
Variance of y*:	16.822	Variance of error:	3.290
Count R2:	0.915	Adj Count R2:	0.190
AIC:	0.874	AIC*n:	175.580
BIC:	-728.523	BIC':	112.691

Full main model for HP2pbfhm for wave= 2

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

Full Nottingham Part 2 HP2pbfhm subscale models

i.educ	_Ieduc_1-8	(naturally coded; _Ieduc_1 omitted)
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note: occ6w2 != 0 predicts failure perfectly
occ6w2 dropped and 9 obs not used

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

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

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

note: movew2 != 0 predicts failure perfectly
movew2 dropped and 39 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw26 omitted because of collinearity

note: bf15 omitted because of collinearity

convergence not achieved

Logistic regression

Number of obs = 291

LR chi2(39) = 121.44

Prob > chi2 = 0.0000

Pseudo R2 = 0.4719

Log likelihood = -67.949794

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0674178	.0282025	2.39	0.017	.0121418	.1226937
_Ieduc_2	22.45919	4.266606	5.26	0.000	14.0968	30.82159
_Ieduc_3	22.06002	4.192694	5.26	0.000	13.84249	30.27755
_Ieduc_4	22.4012	4.329045	5.17	0.000	13.91643	30.88597
_Ieduc_5	22.32897	4.266196	5.23	0.000	13.96738	30.69056
_Ieduc_6	22.02903	4.204125	5.24	0.000	13.7891	30.26897
_Ieduc_7	21.13032	.	.	.	.	.
_Ieduc_8	0	(omitted)				
occ1w2	.9558639	2.824765	0.34	0.735	-4.580574	6.492302
occ2w2	-1.993618	3.01079	-0.66	0.508	-7.894658	3.907421
occ3w2	1.403833	2.850675	0.49	0.622	-4.183387	6.991053
occ4w2	-1.259009	3.02978	-0.42	0.678	-7.197269	4.679252
occ5w2	2.718272	3.09293	0.88	0.379	-3.343759	8.780304
occ6w2	0	(omitted)				
occ7w2	2.384262	2.790736	0.85	0.393	-3.08548	7.854004
occ8w2	1.770943	3.166948	0.56	0.576	-4.436161	7.978046
marrw21	1.861273	1.561449	1.19	0.233	-1.199112	4.921657
marrw22	0	(omitted)				
marrw23	1.290339	1.071559	1.20	0.229	-.8098785	3.390556
marrw25	1.772428	1.596788	1.11	0.267	-1.357219	4.902075
marrw26	0	(omitted)				

inc1w2	-1.33359	2.871884	-0.46	0.642	-6.962379	4.295198
inc2w2	.7173212	2.783801	0.26	0.797	-4.738828	6.17347
inc3w2	.3992103	2.823016	0.14	0.888	-5.133799	5.932219
inc4w2	0	(omitted)				
radhlw2	.0119324	.0102799	1.16	0.246	-.0082157	.0320806
havmil	-.0039166	.0172766	-0.23	0.821	-.0377782	.0299449
avgcumdosew2	.2705886	.2224323	1.22	0.224	-.1653708	.7065479
bf1	-.0266454	.0134122	-1.99	0.047	-.0529327	-.000358
bf4	-.3552675	.0755758	-4.70	0.000	-.5033934	-.2071416
bf6	.0040579	.0115049	0.35	0.724	-.0184912	.026607
bf7	-.0875054	.1502842	-0.58	0.560	-.382057	.2070462
bf14	-.0003758	.000148	-2.54	0.011	-.0006658	-.0000858
bf15	0	(omitted)				
bf40	-.3371788	.1421157	-2.37	0.018	-.6157205	-.0586371
deaw2	-.0553518	.2550262	-0.22	0.828	-.555194	.4444904
dvcew2	-1.208217	2.005762	-0.60	0.547	-5.139437	2.723004
sepaw2	0	(omitted)				
accdw2	-2.803857	1.396614	-2.01	0.045	-5.541171	-.0665435
movew2	0	(omitted)				
illw2	.0638975	.2821958	0.23	0.821	-.4891961	.616991
shfamw2	.0165867	.0090719	1.83	0.067	-.0011938	.0343673
shhlw2	.0127277	.0099957	1.27	0.203	-.0068635	.0323189
shjobw2	-.0073696	.0092032	-0.80	0.423	-.0254077	.0106684
shrelaw2	-.0222356	.0112808	-1.97	0.049	-.0443455	-.0001257
suprtw2	-.0212928	.0081756	-2.60	0.009	-.0373168	-.0052689
suchrw2	-.0010117	.0080736	-0.13	0.900	-.0168358	.0148123
havmilsq	-6.45e-06	.0000545	-0.12	0.906	-.0001132	.0001003
_cons	-23.96724	5.098279	-4.70	0.000	-33.95968	-13.97479

Note: 2 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	27	8	35
-	20	236	256
Total	47	244	291

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	57.45%
Specificity	$\Pr(- \sim D)$	96.72%
Positive predictive value	$\Pr(D +)$	77.14%
Negative predictive value	$\Pr(\sim D -)$	92.19%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	3.28%
False - rate for true D	$\Pr(- D)$	42.55%
False + rate for classified +	$\Pr(\sim D +)$	22.86%
False - rate for classified -	$\Pr(D -)$	7.81%

Correctly classified	90.38%
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Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	291
number of covariate patterns =	291
Pearson $\chi^2(250)$ =	229.67
Prob > χ^2 =	0.8173

Measures of Fit for **logit** of HP2pbfhm

Log-Lik Intercept Only:	-128.671	Log-Lik Full Model:	-67.950
D(242):	135.900	LR(39):	121.443
		Prob > LR:	0.000
McFadden's R2:	0.472	McFadden's Adj R2:	0.091
Maximum Likelihood R2:	0.341	Cragg & Uhler's R2:	0.581
McKelvey and Zavoina's R2:	0.820	Efron's R2:	0.487
Variance of y^* :	18.247	Variance of error:	3.290
Count R2:	0.904	Adj Count R2:	0.404
AIC:	0.804	AIC*n:	233.900
BIC:	-1237.045	BIC':	99.817

Full main model for HP2sxlife for wave= 2

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

Full Nottingham Part 2 HP2sxlife subscale models

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

note: _Ieduc_4 != 0 predicts failure perfectly
_Ieduc_4 dropped and 12 obs not used

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

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 43 obs not used

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

note: marrw25 != 0 predicts failure perfectly
marrw25 dropped and 4 obs not used

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 3 obs not used

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

note: _Ieduc_8 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	248
	LR chi2(38)	=	124.45
	Prob > chi2	=	0.0000
Log likelihood = -81.459667	Pseudo R2	=	0.4331

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.045416	.0245513	1.85	0.064	-.0027037	.0935357
_Ieduc_2	-.0646877	2.529828	-0.03	0.980	-5.02306	4.893684
_Ieduc_3	-.2043117	2.425172	-0.08	0.933	-4.957562	4.548938
_Ieduc_4	0	(omitted)				
_Ieduc_5	.5468814	2.47638	0.22	0.825	-4.306734	5.400497
_Ieduc_6	-.5396204	2.395021	-0.23	0.822	-5.233776	4.154535
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occl1w2	-.914781	4.041769	-0.23	0.821	-8.836503	7.006941
occ2w2	-1.085289	4.050896	-0.27	0.789	-9.024899	6.854322
occ3w2	-2.01676	4.099586	-0.49	0.623	-10.0518	6.018282
occ4w2	-1.281739	4.07837	-0.31	0.753	-9.275197	6.711719
occ5w2	-2.386463	4.187943	-0.57	0.569	-10.59468	5.821754
occ6w2	1.041656	4.356584	0.24	0.811	-7.497091	9.580403

occ7w2	-.2042994	4.128602	-0.05	0.961	-8.296212	7.887613
occ8w2	0	(omitted)				
marrw21	11.19923	1268.681	0.01	0.993	-2475.369	2497.767
marrw22	0	(omitted)				
marrw23	11.00787	1268.681	0.01	0.993	-2475.56	2497.576
marrw25	0	(omitted)				
marrw26	9.989133	1268.682	0.01	0.994	-2476.582	2496.56
inclw2	2.592204	4.16321	0.62	0.534	-5.567537	10.75195
inc2w2	3.029964	4.086266	0.74	0.458	-4.978969	11.0389
inc3w2	2.803138	4.089233	0.69	0.493	-5.211611	10.81789
inc4w2	0	(omitted)				
radhlw2	.0158792	.0090915	1.75	0.081	-.0019397	.0336982
havmil	-.0002765	.0085069	-0.03	0.974	-.0169497	.0163966
avgcumdosew2	-.0370642	.0826057	-0.45	0.654	-.1989685	.1248401
bf1	.0019651	.0129727	0.15	0.880	-.0234608	.0273911
bf4	-.2487796	.05911	-4.21	0.000	-.3646331	-.1329261
bf6	.0163867	.0108586	1.51	0.131	-.0048957	.0376692
bf7	.0671464	.105745	0.63	0.525	-.1401099	.2744028
bf14	-.0000488	.0000798	-0.61	0.541	-.0002053	.0001076
bf15	0	(omitted)				
bf40	.3417099	.1521463	2.25	0.025	.0435086	.6399112
deaw2	.0342021	.3561465	0.10	0.923	-.6638321	.7322364
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0684013	.5282538	-0.13	0.897	-1.10376	.9669571
movew2	.1688384	.5667796	0.30	0.766	-.9420292	1.279706
illw2	.2358444	.3235455	0.73	0.466	-.398293	.8699819
shfamw2	-.0126799	.0083767	-1.51	0.130	-.0290979	.0037381
shhlw2	-.01343	.0100141	-1.34	0.180	-.0330573	.0061973
shjobw2	.0172317	.0096379	1.79	0.074	-.0016582	.0361216
shrelaw2	-.0093206	.0085022	-1.10	0.273	-.0259847	.0073434
suprtw2	.0077123	.0077451	1.00	0.319	-.0074679	.0228925
suchrw2	.0029045	.0070402	0.41	0.680	-.0108941	.016703
havmilsq	-1.32e-06	.0000139	-0.10	0.924	-.0000286	.0000259
_cons	-16.32451	1268.684	-0.01	0.990	-2502.9	2470.251

Logistic model for HP2sxlif

Classified	True		Total
	D	~D	
+	47	15	62
-	19	167	186
Total	66	182	248

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

Sensitivity	$\Pr(+ D)$	71.21%
Specificity	$\Pr(- \sim D)$	91.76%
Positive predictive value	$\Pr(D +)$	75.81%
Negative predictive value	$\Pr(\sim D -)$	89.78%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	8.24%
False - rate for true D	$\Pr(- D)$	28.79%
False + rate for classified +	$\Pr(\sim D +)$	24.19%
False - rate for classified -	$\Pr(D -)$	10.22%

Correctly classified	86.29%
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Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	248
number of covariate patterns =	248
Pearson $\chi^2(209)$ =	320.07
Prob > χ^2 =	0.0000

Measures of Fit for **logit** of HP2sxlife

Log-Lik Intercept Only:	-143.684	Log-Lik Full Model:	-81.460
D(199):	162.919	LR(38):	124.448
		Prob > LR:	0.000
McFadden's R2:	0.433	McFadden's Adj R2:	0.092
Maximum Likelihood R2:	0.395	Cragg & Uhler's R2:	0.575
McKelvey and Zavoina's R2:	0.701	Efron's R2:	0.489
Variance of y*:	11.005	Variance of error:	3.290
Count R2:	0.863	Adj Count R2:	0.485
AIC:	1.052	AIC*n:	260.919
BIC:	-934.253	BIC':	85.062

Full main model for HP2sxlife for wave= 2

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

Full Nottingham Part 2 HP2sxlife subscale models

i.educ	_Ieduc_1-8	(naturally coded; _Ieduc_1 omitted)
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note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression

Number of obs = 362
LR chi2(45) = 172.53
Prob > chi2 = 0.0000
Pseudo R2 = 0.4182

Log likelihood = -119.99963

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0946676	.020348	4.65	0.000	.0547862	.1345489
_Ieduc_2	-12.06916	856.9725	-0.01	0.989	-1691.704	1667.566
_Ieduc_3	-10.96566	856.9724	-0.01	0.990	-1690.601	1668.669
_Ieduc_4	-10.2721	856.9727	-0.01	0.990	-1689.908	1669.364
_Ieduc_5	-11.78295	856.9726	-0.01	0.989	-1691.418	1667.853
_Ieduc_6	-10.87488	856.9725	-0.01	0.990	-1690.51	1668.76
_Ieduc_7	-10.54712	856.9809	-0.01	0.990	-1690.199	1669.105
_Ieduc_8	0	(omitted)				
occ1w2	-1.924676	1.67129	-1.15	0.249	-5.200344	1.350992
occ2w2	-1.071334	1.695639	-0.63	0.528	-4.394725	2.252058
occ3w2	-.4988122	1.696518	-0.29	0.769	-3.823926	2.826301
occ4w2	-.6837643	1.779367	-0.38	0.701	-4.171259	2.803731
occ5w2	-.8653809	1.874647	-0.46	0.644	-4.539621	2.80886
occ6w2	-1.70777	1.969995	-0.87	0.386	-5.568889	2.153348
occ7w2	-.9209399	1.641247	-0.56	0.575	-4.137725	2.295845
occ8w2	-.5235734	1.936624	-0.27	0.787	-4.319287	3.272141
marrw21	-.4474367	1.15873	-0.39	0.699	-2.718505	1.823632
marrw22	-.2713813	1.430959	-0.19	0.850	-3.07601	2.533247
marrw23	-.6859987	.8247327	-0.83	0.406	-2.302445	.9304478
marrw25	-1.534831	1.287976	-1.19	0.233	-4.059218	.9895558
marrw26	0	(omitted)				
inclw2	.1793057	1.714781	0.10	0.917	-3.181602	3.540214
inc2w2	.5322943	1.648367	0.32	0.747	-2.698446	3.763035
inc3w2	-.4148838	1.696991	-0.24	0.807	-3.740924	2.911157
inc4w2	-.3610821	2.088477	-0.17	0.863	-4.454421	3.732257
radhlw2	.0084415	.0066869	1.26	0.207	-.0046645	.0215475
havmil	-.0012719	.0033206	-0.38	0.702	-.0077802	.0052364
avgcumdosew2	.131101	.1238204	1.06	0.290	-.1115826	.3737846
bf1	-.0011966	.0090476	-0.13	0.895	-.0189295	.0165364
bf4	-.1626538	.0410542	-3.96	0.000	-.2431185	-.0821891
bf6	-.0040259	.0075131	-0.54	0.592	-.0187513	.0106995
bf7	-.07395	.0811067	-0.91	0.362	-.2329163	.0850162
bf14	-.000028	.0000759	-0.37	0.712	-.0001769	.0001208
bf15	0	(omitted)				
bf40	.0142117	.0784184	0.18	0.856	-.1394855	.1679089
deaw2	.0365782	.2150994	0.17	0.865	-.3850089	.4581654
dvcew2	-.8025004	1.585115	-0.51	0.613	-3.909268	2.304268

sepaw2	-.5574826	2.582905	-0.22	0.829	-5.619883	4.504918
accdw2	-.5477504	.6503834	-0.84	0.400	-1.822478	.7269777
movew2	.1966685	.5120534	0.38	0.701	-.8069378	1.200275
illw2	.5493357	.2439985	2.25	0.024	.0711074	1.027564
shfamw2	.0017721	.0066016	0.27	0.788	-.0111667	.0147109
shhlw2	.0069859	.006691	1.04	0.296	-.0061281	.0201
shjobw2	-.0075261	.0063225	-1.19	0.234	-.019918	.0048658
shrelaw2	-.0137558	.0073868	-1.86	0.063	-.0282337	.000722
suprtw2	-.0141433	.0055222	-2.56	0.010	-.0249667	-.0033199
suchrw2	.0162332	.0063006	2.58	0.010	.0038842	.0285821
havmilsq	-1.92e-07	2.92e-06	-0.07	0.948	-5.91e-06	5.53e-06
_cons	7.796544	856.9744	0.01	0.993	-1671.842	1687.436

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	59	19	78
-	34	250	284
Total	93	269	362

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

Sensitivity	$\Pr(+ D)$	63.44%
Specificity	$\Pr(- \sim D)$	92.94%
Positive predictive value	$\Pr(D +)$	75.64%
Negative predictive value	$\Pr(\sim D -)$	88.03%
False + rate for true ~D	$\Pr(+ \sim D)$	7.06%
False - rate for true D	$\Pr(- D)$	36.56%
False + rate for classified +	$\Pr(\sim D +)$	24.36%
False - rate for classified -	$\Pr(D -)$	11.97%
Correctly classified		85.36%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	362
number of covariate patterns =	362
Pearson chi2(316) =	350.60
Prob > chi2 =	0.0877

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-120.000
D(313):	239.999	LR(45):	172.533
		Prob > LR:	0.000
McFadden's R2:	0.418	McFadden's Adj R2:	0.181
Maximum Likelihood R2:	0.379	Cragg & Uhler's R2:	0.557
McKelvey and Zavoina's R2:	0.643	Efron's R2:	0.461
Variance of y*:	9.209	Variance of error:	3.290
Count R2:	0.854	Adj Count R2:	0.430
AIC:	0.934	AIC*n:	337.999
BIC:	-1604.085	BIC':	92.591

Full main model for HP2inthob for wave= 2

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

Full Nottingham Part 2 HP2inthob subscale models

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

note: _Ieduc_4 != 0 predicts failure perfectly

 _Ieduc_4 dropped and 12 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ6w2 != 0 predicts failure perfectly

 occ6w2 dropped and 4 obs not used

note: occ8w2 != 0 predicts failure perfectly

 occ8w2 dropped and 43 obs not used

note: marrw22 != 0 predicts failure perfectly

 marrw22 dropped and 7 obs not used

note: marrw25 != 0 predicts failure perfectly

 marrw25 dropped and 4 obs not used

note: marrw26 != 0 predicts failure perfectly

 marrw26 dropped and 3 obs not used

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 3 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	240
	LR chi2(35)	=	92.50
	Prob > chi2	=	0.0000
Log likelihood = -55.199011	Pseudo R2	=	0.4559

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0625698	.0339541	1.84	0.065	-.0039791	.1291186
_Ieduc_2	-1.043358	1.579537	-0.66	0.509	-4.139194	2.052478
_Ieduc_3	-1.383026	.8161024	-1.69	0.090	-2.982558	.216505
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.3882601	.890757	-0.44	0.663	-2.134112	1.357591
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-1.033982	5.222537	-0.20	0.843	-11.26997	9.202003
occ2w2	-2.764859	5.282979	-0.52	0.601	-13.11931	7.58959
occ3w2	-1.159373	5.266774	-0.22	0.826	-11.48206	9.163314
occ4w2	-1.475817	5.272908	-0.28	0.780	-11.81053	8.858893
occ5w2	.6777917	5.260041	0.13	0.897	-9.631698	10.98728
occ6w2	0	(omitted)				
occ7w2	-.3442089	5.327123	-0.06	0.948	-10.78518	10.09676
occ8w2	0	(omitted)				
marrw21	13.93224	1621.282	0.01	0.993	-3163.721	3191.586
marrw22	0	(omitted)				
marrw23	11.47436	1621.282	0.01	0.994	-3166.179	3189.128
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inc1w2	-2.09725	5.429773	-0.39	0.699	-12.73941	8.544909
inc2w2	-.9256519	5.257192	-0.18	0.860	-11.22956	9.378255
inc3w2	.0745765	5.245026	0.01	0.989	-10.20548	10.35464
inc4w2	0	(omitted)				
radhlw2	.0364231	.0131057	2.78	0.005	.0107363	.0621099
havmil	.0020332	.0091412	0.22	0.824	-.0158833	.0199497
avgcumdosew2	-.2023055	.3376483	-0.60	0.549	-.8640841	.4594731
bf1	.0108557	.0182727	0.59	0.552	-.0249582	.0466696

bf4	-.290932	.0816796	-3.56	0.000	-.4510211	-.1308428
bf6	.0111353	.0131635	0.85	0.398	-.0146647	.0369353
bf7	.0337038	.1171208	0.29	0.774	-.1958487	.2632562
bf14	-.000219	.0001127	-1.94	0.052	-.0004398	1.92e-06
bf15	0	(omitted)				
bf40	.490857	.2032201	2.42	0.016	.0925529	.889161
deaw2	.006222	.5178905	0.01	0.990	-1.008825	1.021269
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	1.036869	.5663339	1.83	0.067	-.0731249	2.146863
movew2	.7948452	.8450104	0.94	0.347	-.8613447	2.451035
illw2	-.8262786	.5178561	-1.60	0.111	-1.841258	.1887007
shfamw2	-.003778	.0101348	-0.37	0.709	-.0236419	.0160858
shhlw2	-.0014472	.0125099	-0.12	0.908	-.0259662	.0230717
shjobw2	.0044446	.012101	0.37	0.713	-.0192728	.0281621
shrelaw2	-.0158848	.0098629	-1.61	0.107	-.0352157	.0034461
suprtw2	-.0048211	.0089741	-0.54	0.591	-.0224099	.0127678
suchrw2	.016543	.008867	1.87	0.062	-.0008361	.033922
havmilsq	-2.84e-06	.0000159	-0.18	0.858	-.000034	.0000283
_cons	-16.47971	1621.283	-0.01	0.992	-3194.136	3161.177

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	20	6	26
-	16	198	214
Total	36	204	240

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	55.56%
Specificity	$\Pr(- \sim D)$	97.06%
Positive predictive value	$\Pr(D +)$	76.92%
Negative predictive value	$\Pr(\sim D -)$	92.52%
False + rate for true ~D	$\Pr(+ \sim D)$	2.94%
False - rate for true D	$\Pr(- D)$	44.44%
False + rate for classified +	$\Pr(\sim D +)$	23.08%
False - rate for classified -	$\Pr(D -)$	7.48%
Correctly classified		90.83%

Logistic model for HP2inthob, goodness-of-fit test

```
number of observations =      240
number of covariate patterns =    240
    Pearson chi2(204) =    545.84
        Prob > chi2 =      0.0000
```

Measures of Fit for logit of HP2inthob

Log-Lik Intercept Only:	-101.450	Log-Lik Full Model:	-55.199
D(191):	110.398	LR(35):	92.502
		Prob > LR:	0.000
McFadden's R2:	0.456	McFadden's Adj R2:	-0.027
Maximum Likelihood R2:	0.320	Cragg & Uhler's R2:	0.561
McKelvey and Zavoina's R2:	0.776	Efron's R2:	0.482
Variance of y*:	14.694	Variance of error:	3.290
Count R2:	0.908	Adj Count R2:	0.389
AIC:	0.868	AIC*n:	208.398
BIC:	-936.404	BIC':	99.320

Full main model for HP2inthob for wave= 2

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

Full Nottingham Part 2 HP2inthob subscale models

```
i.educ          _Ieduc_1-8          (naturally coded; _Ieduc_1 omitted)
note: sepaw2 != 0 predicts failure perfectly
      sepaw2 dropped and 8 obs not used
```

```
note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity
```

Logistic regression	Number of obs	=	354
	LR chi2(44)	=	115.47
	Prob > chi2	=	0.0000
Log likelihood = -111.06431	Pseudo R2	=	0.3420

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.079863	.021131	3.78	0.000	.0384469	.121279
_Ieduc_2	-12.93831	1490.754	-0.01	0.993	-2934.762	2908.885
_Ieduc_3	-12.4076	1490.754	-0.01	0.993	-2934.231	2909.416
_Ieduc_4	-11.72169	1490.754	-0.01	0.994	-2933.546	2910.102
_Ieduc_5	-12.09518	1490.754	-0.01	0.994	-2933.919	2909.728
_Ieduc_6	-12.44516	1490.754	-0.01	0.993	-2934.269	2909.378
_Ieduc_7	-12.06531	1490.757	-0.01	0.994	-2933.895	2909.764
_Ieduc_8	0	(omitted)				
occ1w2	-1.681778	1.842381	-0.91	0.361	-5.292779	1.929222
occ2w2	-2.066763	1.905083	-1.08	0.278	-5.800657	1.66713
occ3w2	-.925484	1.867622	-0.50	0.620	-4.585956	2.734988
occ4w2	-1.837685	1.997812	-0.92	0.358	-5.753324	2.077954
occ5w2	-1.808015	2.160492	-0.84	0.403	-6.042501	2.426471
occ6w2	-.7980572	2.0458	-0.39	0.696	-4.807751	3.211637
occ7w2	-.6513668	1.8133	-0.36	0.719	-4.205369	2.902636
occ8w2	-.7497523	2.02704	-0.37	0.711	-4.722678	3.223174
marrw21	1.330155	1.130799	1.18	0.239	-.8861701	3.546479
marrw22	.1433998	1.421047	0.10	0.920	-2.641801	2.9286
marrw23	.3124211	.8029396	0.39	0.697	-1.261312	1.886154
marrw25	.2321157	1.213839	0.19	0.848	-2.146964	2.611196
marrw26	0	(omitted)				
inclw2	1.002608	1.857433	0.54	0.589	-2.637893	4.643109
inc2w2	1.21648	1.809887	0.67	0.502	-2.330833	4.763793
inc3w2	.8716928	1.845137	0.47	0.637	-2.744709	4.488095
inc4w2	2.25991	2.119136	1.07	0.286	-1.893519	6.41334
radhlw2	.0169047	.0075432	2.24	0.025	.0021202	.0316892
havmil	.0026206	.00401	0.65	0.513	-.0052388	.0104801
avgcumdosew2	.1098391	.1075167	1.02	0.307	-.1008897	.3205679
bf1	-.0101735	.0098443	-1.03	0.301	-.029468	.0091209
bf4	-.160166	.0433489	-3.69	0.000	-.2451282	-.0752038
bf6	-.0029228	.0086097	-0.34	0.734	-.0197974	.0139519
bf7	-.0201783	.0882604	-0.23	0.819	-.1931656	.152809
bf14	-.0000789	.0000837	-0.94	0.346	-.000243	.0000853
bf15	0	(omitted)				
bf40	-.0387073	.0922777	-0.42	0.675	-.2195682	.1421537
deaw2	.1202612	.2113024	0.57	0.569	-.2938838	.5344063
dvcew2	.0143372	1.477099	0.01	0.992	-2.880724	2.909399
sepaw2	0	(omitted)				
accdw2	.4772298	.6036102	0.79	0.429	-.7058243	1.660284
movew2	-.5141092	.7928535	-0.65	0.517	-2.068073	1.039855
illw2	.1586699	.2249295	0.71	0.481	-.2821838	.5995235
shfamw2	-.0005225	.0071722	-0.07	0.942	-.0145799	.0135348
shhlw2	.0069143	.0072142	0.96	0.338	-.0072252	.0210539
shjobw2	-.0096031	.0066833	-1.44	0.151	-.0227021	.003496
shrelaw2	-.011349	.0077316	-1.47	0.142	-.0265027	.0038047
suprtw2	-.01257	.0057932	-2.17	0.030	-.0239246	-.0012155

suchrw2	.000171	.0063873	0.03	0.979	-.0123478	.0126898
havmilsq	-2.75e-06	5.84e-06	-0.47	0.638	-.0000142	8.69e-06
_cons	8.21905	1490.755	0.01	0.996	-2913.607	2930.045

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	35	12	47
-	30	277	307
Total	65	289	354

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	53.85%
Specificity	$\Pr(- \sim D)$	95.85%
Positive predictive value	$\Pr(D +)$	74.47%
Negative predictive value	$\Pr(\sim D -)$	90.23%
False + rate for true ~D	$\Pr(+ \sim D)$	4.15%
False - rate for true D	$\Pr(- D)$	46.15%
False + rate for classified +	$\Pr(\sim D +)$	25.53%
False - rate for classified -	$\Pr(D -)$	9.77%
Correctly classified		88.14%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	354
number of covariate patterns =	354
Pearson chi2(309) =	384.69
Prob > chi2 =	0.0022

Measures of Fit for **logit** of HP2inthob

Log-Lik Intercept Only:	-168.799	Log-Lik Full Model:	-111.064
D(305):	222.129	LR(44):	115.469
		Prob > LR:	0.000
McFadden's R2:	0.342	McFadden's Adj R2:	0.052
Maximum Likelihood R2:	0.278	Cragg & Uhler's R2:	0.453
McKelvey and Zavoina's R2:	0.619	Efron's R2:	0.372
Variance of y*:	8.629	Variance of error:	3.290
Count R2:	0.881	Adj Count R2:	0.354
AIC:	0.904	AIC*n:	320.129
BIC:	-1568.007	BIC':	142.780

Full main model for HP2vacatn for wave= 2

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

Full Nottingham Part 2 HP2vacatn subscale models

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

note: _Ieduc_4 != 0 predicts failure perfectly

 _Ieduc_4 dropped and 12 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ6w2 != 0 predicts failure perfectly

 occ6w2 dropped and 4 obs not used

note: occ8w2 != 0 predicts failure perfectly

 occ8w2 dropped and 43 obs not used

note: marrw22 != 0 predicts failure perfectly

 marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly

 marrw26 dropped and 3 obs not used

note: inclw2 != 0 predicts failure perfectly

 inclw2 dropped and 15 obs not used

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

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

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 2 obs not used

note: _Ieduc_6 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	226
	LR chi2(34)	=	89.37
	Prob > chi2	=	0.0000
Log likelihood = -56.061123	Pseudo R2	=	0.4435

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0518481	.0320007	1.62	0.105	-.0108721	.1145682
_Ieduc_2	-.8995561	1.385138	-0.65	0.516	-3.614377	1.815265
_Ieduc_3	-.9705268	.7645926	-1.27	0.204	-2.469101	.5280471
_Ieduc_4	0	(omitted)				
_Ieduc_5	.2832276	.9129115	0.31	0.756	-1.506046	2.072501
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	.8106927	4.39778	0.18	0.854	-7.808798	9.430184
occ2w2	.6920438	4.410202	0.16	0.875	-7.951794	9.335881
occ3w2	.1305127	4.486304	0.03	0.977	-8.662482	8.923507
occ4w2	.89698	4.456507	0.20	0.840	-7.837613	9.631573
occ5w2	2.521801	4.487812	0.56	0.574	-6.274149	11.31775
occ6w2	0	(omitted)				
occ7w2	-.3588464	4.557173	-0.08	0.937	-9.290741	8.573048
occ8w2	0	(omitted)				
marrw21	-2.421712	1.8269	-1.33	0.185	-6.002369	1.158946
marrw22	0	(omitted)				
marrw23	-3.630848	1.854766	-1.96	0.050	-7.266123	.0044279
marrw25	0	(omitted)				
marrw26	0	(omitted)				
incl1w2	0	(omitted)				
inc2w2	1.85842	4.404089	0.42	0.673	-6.773436	10.49027
inc3w2	2.742231	4.406664	0.62	0.534	-5.894672	11.37913
inc4w2	0	(omitted)				
radhlw2	.0040453	.0113057	0.36	0.720	-.0181135	.0262041

havmil	.0057124	.0149305	0.38	0.702	-.0235508	.0349756
avgcumdosew2	-.2290056	.2971244	-0.77	0.441	-.8113587	.3533474
bf1	-.0014462	.0165487	-0.09	0.930	-.0338809	.0309886
bf4	-.3542988	.0849763	-4.17	0.000	-.5208492	-.1877483
bf6	.0330318	.0142347	2.32	0.020	.0051324	.0609312
bf7	.138525	.1284222	1.08	0.281	-.1131778	.3902278
bf14	-.0001823	.0001057	-1.72	0.085	-.0003895	.0000249
bf15	0	(omitted)				
bf40	.7151656	.2261712	3.16	0.002	.2718781	1.158453
deaw2	-.1293481	.4547459	-0.28	0.776	-1.020634	.7619374
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	.6561002	.566831	1.16	0.247	-.4548681	1.767069
movew2	.8988969	.8083424	1.11	0.266	-.6854251	2.483219
illw2	-.1907347	.4011558	-0.48	0.634	-.9769857	.5955162
shfamw2	.0075499	.0104385	0.72	0.470	-.0129092	.0280089
shhlw2	-.0086364	.01369	-0.63	0.528	-.0354682	.0181955
shjobw2	-.0142832	.0135576	-1.05	0.292	-.0408556	.0122892
shrelaw2	-.0233172	.0117345	-1.99	0.047	-.0463164	-.000318
suprtw2	.0076256	.010193	0.75	0.454	-.0123524	.0276036
suchrw2	-.0031525	.0091098	-0.35	0.729	-.0210073	.0147023
havmilsq	-.00002	.0000344	-0.58	0.560	-.0000874	.0000473
_cons	-2.643954	3.239572	-0.82	0.414	-8.993397	3.70549

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	23	5	28
-	14	184	198
Total	37	189	226

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

True D defined as HP2vacatn != 0

Sensitivity	$\Pr(+ D)$	62.16%
Specificity	$\Pr(- \sim D)$	97.35%
Positive predictive value	$\Pr(D +)$	82.14%
Negative predictive value	$\Pr(\sim D -)$	92.93%
False + rate for true ~D	$\Pr(+ \sim D)$	2.65%
False - rate for true D	$\Pr(- D)$	37.84%
False + rate for classified +	$\Pr(\sim D +)$	17.86%
False - rate for classified -	$\Pr(D -)$	7.07%

Correctly classified **91.59%**

Logistic model for HP2vacatn, goodness-of-fit test

number of observations = **226**
number of covariate patterns = **226**
Pearson chi2(191) = **516.74**
Prob > chi2 = **0.0000**

Measures of Fit for **logit** of **HP2vacatn**

Log-Lik Intercept Only:	-100.747	Log-Lik Full Model:	-56.061
D(177):	112.122	LR(34):	89.371
		Prob > LR:	0.000
McFadden's R2:	0.444	McFadden's Adj R2:	-0.043
Maximum Likelihood R2:	0.327	Cragg & Uhler's R2:	0.554
McKelvey and Zavoina's R2:	0.764	Efron's R2:	0.489
Variance of y*:	13.933	Variance of error:	3.290
Count R2:	0.916	Adj Count R2:	0.486
AIC:	0.930	AIC*n:	210.122
BIC:	-847.312	BIC':	94.927

Full main model for HP2vacatn for wave= 2

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

Full Nottingham Part 2 HP2vacatn subscale models

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
note: sepaw2 != 0 predicts failure perfectly
 sepaw2 dropped and 8 obs not used

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	354
	LR chi2(44)	=	111.91
	Prob > chi2	=	0.0000
Log likelihood = -108.2809	Pseudo R2	=	0.3407

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0893137	.0216493	4.13	0.000	.0468818	.1317456
_Ieduc_2	-14.53546	998.8236	-0.01	0.988	-1972.194	1943.123
_Ieduc_3	-14.6778	998.8236	-0.01	0.988	-1972.336	1942.981
_Ieduc_4	-12.98634	998.8239	-0.01	0.990	-1970.645	1944.672
_Ieduc_5	-14.15108	998.8238	-0.01	0.989	-1971.81	1943.508
_Ieduc_6	-14.14507	998.8236	-0.01	0.989	-1971.803	1943.513
_Ieduc_7	-14.60252	998.8256	-0.01	0.988	-1972.265	1943.06
_Ieduc_8	0	(omitted)				
occ1w2	-.862164	2.392979	-0.36	0.719	-5.552316	3.827988
occ2w2	.000175	2.407446	0.00	1.000	-4.718332	4.718682
occ3w2	.0954163	2.407091	0.04	0.968	-4.622395	4.813227
occ4w2	-.7520064	2.479333	-0.30	0.762	-5.61141	4.107398
occ5w2	-.8008531	2.678457	-0.30	0.765	-6.050532	4.448826
occ6w2	-.120062	2.547159	-0.05	0.962	-5.112401	4.872278
occ7w2	.0075488	2.349651	0.00	0.997	-4.597682	4.61278
occ8w2	1.363519	2.668018	0.51	0.609	-3.8657	6.592739
marrw21	.0044997	1.254312	0.00	0.997	-2.453907	2.462906
marrw22	-.1027305	1.362298	-0.08	0.940	-2.772785	2.567324
marrw23	.1467459	.8080411	0.18	0.856	-1.436986	1.730477
marrw25	.0219803	1.235341	0.02	0.986	-2.399244	2.443205
marrw26	0	(omitted)				
inclw2	-.4927145	2.398088	-0.21	0.837	-5.192881	4.207452
inc2w2	.280804	2.359963	0.12	0.905	-4.344638	4.906246
inc3w2	.1828947	2.366651	0.08	0.938	-4.455656	4.821445
inc4w2	-.2400624	2.690874	-0.09	0.929	-5.514079	5.033954
radhlw2	.0222207	.0077189	2.88	0.004	.0070919	.0373496
havmil	.0004923	.0030889	0.16	0.873	-.0055619	.0065465
avgcumdosew2	.0521813	.1224679	0.43	0.670	-.1878514	.2922141
bf1	-.0290072	.0107044	-2.71	0.007	-.0499874	-.0080269
bf4	-.1358474	.0436692	-3.11	0.002	-.2214376	-.0502573
bf6	.0008464	.0089639	0.09	0.925	-.0167225	.0184153
bf7	.091511	.0838763	1.09	0.275	-.0728836	.2559055
bf14	-.0001329	.0000932	-1.43	0.154	-.0003155	.0000496
bf15	0	(omitted)				
bf40	-.088322	.1002957	-0.88	0.379	-.2848979	.1082539
deaw2	.2253226	.214436	1.05	0.293	-.1949642	.6456094
dvcew2	1.943345	1.290529	1.51	0.132	-.5860453	4.472735
sepaw2	0	(omitted)				
accdw2	-.5786213	.7839833	-0.74	0.460	-2.1152	.9579576
movew2	.0523756	.7206426	0.07	0.942	-1.360058	1.464809
illw2	.3527103	.2271102	1.55	0.120	-.0924176	.7978382
shfamw2	.0116122	.0069058	1.68	0.093	-.001923	.0251474
shhlw2	.0049385	.0075176	0.66	0.511	-.0097958	.0196728
shjobw2	-.0062545	.006891	-0.91	0.364	-.0197605	.0072516
shrelaw2	-.0200226	.0083906	-2.39	0.017	-.0364678	-.0035773
suprtw2	-.0064369	.005962	-1.08	0.280	-.0181221	.0052483

suchrw2	.0058273	.0067013	0.87	0.385	-.0073069	.0189615
havmilsq	-8.06e-07	2.86e-06	-0.28	0.778	-6.41e-06	4.80e-06
_cons	9.013612	998.8259	0.01	0.993	-1948.649	1966.676

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	31	10	41
-	31	282	313
Total	62	292	354

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

True D defined as HP2vacatn != 0

Sensitivity	$\Pr(+ D)$	50.00%
Specificity	$\Pr(- \sim D)$	96.58%
Positive predictive value	$\Pr(D +)$	75.61%
Negative predictive value	$\Pr(\sim D -)$	90.10%

False + rate for true ~D	$\Pr(+ \sim D)$	3.42%
False - rate for true D	$\Pr(- D)$	50.00%
False + rate for classified +	$\Pr(\sim D +)$	24.39%
False - rate for classified -	$\Pr(D -)$	9.90%

Correctly classified	88.42%
----------------------	--------

Logistic model for HP2vacatn, goodness-of-fit test

number of observations =	354
number of covariate patterns =	354
Pearson chi2(309) =	372.41
Prob > chi2 =	0.0077

Measures of Fit for **logit** of HP2vacatn

```
120 .
121 . set more off

122 . *-----Chunk 2 dosew2 moderator paid employment impact-----
    > ----
123 . title "1.  H1 pt2 wv 2 male cum rad dose wrt HP2work impact "
```

17 Jun 2012 10:03:32 ***

```

124 . * male models
125 .       forvalues j = 2/2 {
      2.       set more off
      3. title4 "trimmed HP2work main effects models wave 2 for H1 part 2 with dos
> e ns"
      4. title4 "Wave `j' dose HP2work relationship but avgcumdosew`j': Dose not s
> ignif"
      5. di _skip(2)
      6. di as input "Gender =1 HP2work model"
      7.       logit HP2work age bf4 bf40 illw`j' movew`j' shrelaw`j' ///
>       avgcumdosew`j' radhlw`j' if gender==1
      8.               estat class
      9.               estat gof
     10.               fitstat
     11. }

```

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

Wave 2 dose HP2work relationship but avgcumdosew2: Dose not signif

Gender =1 HP2work model

```

Iteration 0:  log likelihood = -172.64201
Iteration 1:  log likelihood = -143.10953
Iteration 2:  log likelihood = -140.75282
Iteration 3:  log likelihood = -140.73717
Iteration 4:  log likelihood = -140.73717

```

Logistic regression	Number of obs	=	339
	LR chi2(8)	=	63.81
	Prob > chi2	=	0.0000
Log likelihood = -140.73717	Pseudo R2	=	0.1848

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0047169	.0143138	0.33	0.742	-.0233376	.0327714
bf4	-.1503587	.0356506	-4.22	0.000	-.2202327	-.0804848
bf40	.3523359	.1019141	3.46	0.001	.1525879	.5520839
illw2	-.0335556	.2419386	-0.14	0.890	-.5077465	.4406354
movew2	.5741457	.3222115	1.78	0.075	-.0573772	1.205669
shrelaw2	-.007559	.0045614	-1.66	0.097	-.0164991	.0013811
avgcumdosew2	.0038936	.0526483	0.07	0.941	-.0992953	.1070824
radhlw2	.00178	.0052528	0.34	0.735	-.0085154	.0120754
_cons	-.7511547	.9928636	-0.76	0.449	-2.697132	1.194822

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	21	13	34
-	49	256	305
Total	70	269	339

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

Sensitivity	$\Pr(+ D)$	30.00%
Specificity	$\Pr(- \sim D)$	95.17%
Positive predictive value	$\Pr(D +)$	61.76%
Negative predictive value	$\Pr(\sim D -)$	83.93%
False + rate for true ~D	$\Pr(+ \sim D)$	4.83%
False - rate for true D	$\Pr(- D)$	70.00%
False + rate for classified +	$\Pr(\sim D +)$	38.24%
False - rate for classified -	$\Pr(D -)$	16.07%
Correctly classified		81.71%

Logistic model for HP2work, goodness-of-fit test

number of observations = **339**
 number of covariate patterns = **334**
 Pearson $\chi^2(325)$ = **305.63**
 Prob > χ^2 = **0.7731**

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

Log-Lik Intercept Only:	-172.642	Log-Lik Full Model:	-140.737
D(330):	281.474	LR(8):	63.810
		Prob > LR:	0.000
McFadden's R2:	0.185	McFadden's Adj R2:	0.133
Maximum Likelihood R2:	0.172	Cragg & Uhler's R2:	0.269
McKelvey and Zavoina's R2:	0.282	Efron's R2:	0.184
Variance of y*:	4.584	Variance of error:	3.290
Count R2:	0.817	Adj Count R2:	0.114
AIC:	0.883	AIC*n:	299.474
BIC:	-1641.106	BIC':	-17.202

```

126 .
127 . title4 "Constructing male moderators of HP2work in wave 2"

```

```
Constructing male moderators of HP2work in wave 2
```

```

128 . * construction of potential moderators
129 .
130 . set more off

131 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd2 = `var'*avgcumdosew2
      3. label var `var'Xd2 "interaction of avgcumdosew2 and `var'"
      4. }

132 .
133 .
134 .
135 .
136 . 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)

```

137 . forvalues j = 2/2 {
      2. title4 "trimmed HP2work main effects models wave `j' " "male model for H1
      > part 2 with dose ns"
      3. title2 "Wave `j dose HP2work relationship but avgcumdosew`j': Dose not si
      > gnif"
      4. }

```

```
trimmed HP2work main effects models wave 2
```

```

title2: Wave `j dose HP2work relationship but avgcumdosew2: Dose not signif
Date and time: 17 Jun 2012 10:03:34
Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/hltests/hlpt2
Stata data file: chwide16june2012.dta
> has 2376 variables and 703 observations

```

```
Wave `j dose HP2work relationship but avgcumdosew2: Dose not signif
```

```

138 .
139 .
140 . set more off

141 .
142 . forvalues j = 2/2 {
      2.                sw, pr(.1):logistic HP2work age bf4 bf40 movew`j' shrelaw
> `j'   ///
>                avgcumdosew`j' illw2 radhlw`j' bf4Xd2 bf40Xd2 if gender==1,
> coef
      3.                estat class
      4.                estat gof
      5.                fitstat
      6. }

                        begin with full model
p = 0.9757 >= 0.1000 removing illw2
p = 0.7795 >= 0.1000 removing radhlw2
p = 0.7737 >= 0.1000 removing avgcumdosew2
p = 0.6592 >= 0.1000 removing age
p = 0.3222 >= 0.1000 removing bf40Xd2
p = 0.8752 >= 0.1000 removing bf4Xd2

```

```

Logistic regression                                Number of obs   =       339
                                                    LR chi2(4)       =       63.51
                                                    Prob > chi2      =       0.0000
Log likelihood = -140.88616                      Pseudo R2       =       0.1839

```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw2	-.0075236	.0045549	-1.65	0.099	-.016451	.0014037
bf4	-.1587735	.0291898	-5.44	0.000	-.2159845	-.1015625
bf40	.3608735	.0919302	3.93	0.000	.1806936	.5410534
movew2	.5377149	.3084581	1.74	0.081	-.0668519	1.142282
_cons	-.3430408	.4475445	-0.77	0.443	-1.220212	.5341304

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	21	15	36
-	49	254	303
Total	70	269	339

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

Sensitivity	$\Pr(+ D)$	30.00%
Specificity	$\Pr(- \sim D)$	94.42%
Positive predictive value	$\Pr(D +)$	58.33%
Negative predictive value	$\Pr(\sim D -)$	83.83%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.58%
False - rate for true D	$\Pr(- D)$	70.00%
False + rate for classified +	$\Pr(\sim D +)$	41.67%
False - rate for classified -	$\Pr(D -)$	16.17%
Correctly classified		81.12%

Logistic model for HP2work, goodness-of-fit test

number of observations =	339
number of covariate patterns =	210
Pearson $\chi^2(205)$ =	208.24
Prob > χ^2 =	0.4238

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-172.642	Log-Lik Full Model:	-140.886
D(334):	281.772	LR(4):	63.512
		Prob > LR:	0.000
McFadden's R2:	0.184	McFadden's Adj R2:	0.155
Maximum Likelihood R2:	0.171	Cragg & Uhler's R2:	0.267
McKelvey and Zavoina's R2:	0.279	Efron's R2:	0.182
Variance of y*:	4.565	Variance of error:	3.290
Count R2:	0.811	Adj Count R2:	0.086
AIC:	0.861	AIC*n:	291.772
BIC:	-1664.112	BIC':	-40.208

```

143 .
144 .
145 .
146 . * capturing significant vars from last analysis
147 . local cn1: colnames(e(b))

148 . di "`cn1'"
      shrelaw2 bf4 bf40 movew2 _cons

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

150 . di `leng1'
      30

151 . local leng1b `leng1'-6

152 . di `leng1b'
      24

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

154 . di "`nuvlist'"
      shrelaw2 bf4 bf40 movew2

155 . local rhsvars = "`nuvlist'"

156 . local nuvlist= "`nuvlist'"

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

158 . di "`nuvlist'"
      shrelaw2 bf4 bf40 movew2

159 . sw, pr(.1):logit hp2hmcare `nuvlist' if gender==1
      begin with full model
      p = 0.9705 >= 0.1000 removing movew2
      p = 0.6621 >= 0.1000 removing shrelaw2

Logistic regression                                Number of obs   =       339
                                                    LR chi2(2)      =       81.34
                                                    Prob > chi2     =       0.0000
Log likelihood = -131.97405                        Pseudo R2       =       0.2356

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.1682682	.0893164	1.88	0.060	-.0067887	.3433251
bf4	-.2243001	.0309592	-7.25	0.000	-.2849791	-.1636212
_cons	.7247699	.4549691	1.59	0.111	-.1669531	1.616493

```

160 . di "`rhsvars'"
      shrelaw2 bf4 bf40 movev2

161 . matrix define c=e(b)

162 . local cn2: colnames(c)

163 . di "`cn2'"
      bf40 bf4 _cons

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

165 . local leng2b = `leng2'-6

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

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

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -146.01734
Iteration 2:  log likelihood = -144.08312
Iteration 3:  log likelihood = -144.07356
Iteration 4:  log likelihood = -144.07356

```

Logistic regression	Number of obs	=	340
	LR chi2(2)	=	57.60
	Prob > chi2	=	0.0000
Log likelihood = -144.07356	Pseudo R2	=	0.1666

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.3278445	.0853217	3.84	0.000	.160617	.495072
bf4	-.1439508	.0277538	-5.19	0.000	-.1983472	-.0895544
_cons	-.5378471	.4253878	-1.26	0.206	-1.371592	.2958977

```

168 .
169 .
170 .
171 . di "`rhsvars'"
    bf40 bf4

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

173 . di "`varlist2'"
    bf40 bf4

174 .
175 . * constructing potential moderators
176 . foreach var in age illw2 {
    2. cap gen `var'Xd2 = `var'* avgcumdosew2
    3. }

177 .
178 . *x no signif male moderators for paid employment
179 . set more off

180 . sw, pr(.1): logistic hp2work `rhsvars' illw2Xd2 if gender==1, coef
    begin with full model
    p = 0.3950 >= 0.1000 removing illw2Xd2

```

```

Logistic regression                                Number of obs   =       340
                                                    LR chi2(2)      =       57.60
                                                    Prob > chi2     =       0.0000
Log likelihood = -144.07356                        Pseudo R2      =       0.1666

```

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.3278445	.0853217	3.84	0.000	.160617	.495072
bf4	-.1439508	.0277538	-5.19	0.000	-.1983472	-.0895544
_cons	-.5378471	.4253878	-1.26	0.206	-1.371592	.2958977

181 . fitstat

Measures of Fit for **logistic** of **hp2work**

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-144.074
D(337):	288.147	LR(2):	57.599
		Prob > LR:	0.000
McFadden's R2:	0.167	McFadden's Adj R2:	0.149
Maximum Likelihood R2:	0.156	Cragg & Uhler's R2:	0.244
McKelvey and Zavoina's R2:	0.248	Efron's R2:	0.162
Variance of y*:	4.375	Variance of error:	3.290
Count R2:	0.806	Adj Count R2:	0.057
AIC:	0.865	AIC*n:	294.147
BIC:	-1676.208	BIC':	-45.941

182 .

183 . scalar wkModMw2 = "none"

184 . di _skip(2)

185 . title4 "testing the female moderator model Hp2work H1 Pt 2 wave 2"

testing the female moderator model Hp2work H1 Pt 2 wave 2

186 . * Testing female moderator model xx
> xxxx

187 .

188 . title4 "testing general female moderator model for hp2work"

testing general female moderator model for hp2work

189 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

190 . di _skip(4)

```

191 .
192 . di _skip(4)

193 .
194 . forvalues j = 2/2 {
      2. set more off
      3. di _skip(4)
      4. di as input "For females hp2work on wave 2 with dose ns"
      5. des age occ1w`j' -occ8w`j' inc1w`j' -inc4w`j' avgcumdosew`j' `w2bf'
      6. sw, pr(.1): logistic HP2work age havmilsq ///
>     avgcumdosew2 illw`j' shjobw`j' suprtw`j' radhlw`j' if gender==2, coef
      7. estat gof
      8. estat class
      9. fitstat
     10. }

```

For females hp2work on wave 2 with dose ns

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)

```

bf4          float   %9.0g          bf4 = max(0, 24 - BSIsoma)
bf6          float   %9.0g          bf6= max(0, radtlw2 - 10)
bf7          float   %9.0g          bf7= max(0, 10 - radtlw2)
bf14         float   %9.0g          bf14= max(0, radw2 - 10) * bf12
bf15         float   %9.0g          bf15= max(0, 10 - radw2) * bf12
bf40         float   %9.0g          bf40 = max(0, icdxcnt -
                                     1.01635E-007)

```

```

begin with full model
p = 0.9490 >= 0.1000 removing shjobw2
p = 0.5496 >= 0.1000 removing havmilsq
p = 0.4955 >= 0.1000 removing suprtw2
p = 0.2666 >= 0.1000 removing avgcumdosew2
p = 0.1232 >= 0.1000 removing illw2

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(2)      =       49.29
                                                    Prob > chi2     =       0.0000
Log likelihood = -181.91527                      Pseudo R2      =       0.1193

```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0632993	.0119444	5.30	0.000	.0398887	.08671
radhlw2	.010972	.0040298	2.72	0.006	.0030737	.0188703
_cons	-5.088259	.6777663	-7.51	0.000	-6.416656	-3.759861

Logistic model for HP2work, goodness-of-fit test

```

number of observations =       363
number of covariate patterns =    219
Pearson chi2(216) =    254.55
Prob > chi2 =       0.0370

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	20	7	27
-	73	263	336
Total	93	270	363

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

Sensitivity	$\Pr(+ D)$	21.51%
Specificity	$\Pr(- \sim D)$	97.41%
Positive predictive value	$\Pr(D +)$	74.07%
Negative predictive value	$\Pr(\sim D -)$	78.27%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	2.59%
False - rate for true D	$\Pr(- D)$	78.49%
False + rate for classified +	$\Pr(\sim D +)$	25.93%
False - rate for classified -	$\Pr(D -)$	21.73%
Correctly classified		77.96%

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

Log-Lik Intercept Only:	-206.563	Log-Lik Full Model:	-181.915
D(360):	363.831	LR(2):	49.295
		Prob > LR:	0.000
McFadden's R2:	0.119	McFadden's Adj R2:	0.105
Maximum Likelihood R2:	0.127	Cragg & Uhler's R2:	0.187
McKelvey and Zavoina's R2:	0.205	Efron's R2:	0.150
Variance of y*:	4.139	Variance of error:	3.290
Count R2:	0.780	Adj Count R2:	0.140
AIC:	1.019	AIC*n:	369.831
BIC:	-1758.154	BIC':	-37.506

```

195 .
196 . replace ageXd2 = age*avgcumdosew2
    (0 real changes made)

197 .
198 . * capturing significant vars
199 . local cn3: colnames(e(b))

```

```

200 . di "`cn3'"
      age radhlw2 _cons

201 . local leng3 = length( "`cn3'")

202 . di `leng3'
      17

203 . local leng3b `leng3'-6

204 . di `leng3b'
      11

205 . local nuvlist3 = substr("`cn3'",1,`leng3b')

206 . di "`nuvlist3'"
      age radhlw2

207 . local rhsvars3 = "`nuvlist3'"

208 . local rhsvars4= substr("`cn3'",1,`leng3b')

209 . di "`rhsvars4'"
      age radhlw2

210 .
211 . * moderators for hp2work female and male are saved as scalars:
212 . scalar wkModFw2="none"

213 . scalar wkModMw2="none"

214 . cap gen ageXd2 = age*avgcumdosew2

215 .
216 . *x no significant female moderator for paid employment
217 . forvalues j = 2/2 {
      2. di as input "For females hp2probsoc on wave 2 with dose ns"
      3. des age occlw`j'-occ8w`j' inclw`j'-inc4w`j' avgcumdosew`j'
      4. set more off
      5. sw, pr(.1): logistic HP2work bf4 bf14 age havmil ///
> avgcumdosew2 ageXd2 illw`j' accdw`j' suprtw`j' if gender==2, coef
      6. estat gof
      7. estat class
      8. fitstat
      9. }
For females hp2probsoc on wave 2 with dose ns

```

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

```

begin with full model
p = 0.9295 >= 0.1000 removing suprtw2
p = 0.8298 >= 0.1000 removing ageXd2
p = 0.3867 >= 0.1000 removing havmil
p = 0.4373 >= 0.1000 removing accdw2
p = 0.3450 >= 0.1000 removing illw2
p = 0.1908 >= 0.1000 removing bf14
p = 0.2277 >= 0.1000 removing avgcumdosew2

```

Logistic regression

Log likelihood = -176.56392

```

Number of obs   =      363
LR chi2(2)      =      60.00
Prob > chi2     =      0.0000
Pseudo R2      =      0.1452

```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.111911	.026544	-4.22	0.000	-.1639364	-.0598857
age	.0513174	.012385	4.14	0.000	.0270434	.0755915
_cons	-2.690984	.784746	-3.43	0.001	-4.229058	-1.152911

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      363
number of covariate patterns =    275
Pearson chi2(272) =    304.33
Prob > chi2 =    0.0864

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	31	18	49
-	62	252	314
Total	93	270	363

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

Sensitivity	$\Pr(+ D)$	33.33%
Specificity	$\Pr(- \sim D)$	93.33%
Positive predictive value	$\Pr(D +)$	63.27%
Negative predictive value	$\Pr(\sim D -)$	80.25%
False + rate for true ~D	$\Pr(+ \sim D)$	6.67%
False - rate for true D	$\Pr(- D)$	66.67%
False + rate for classified +	$\Pr(\sim D +)$	36.73%
False - rate for classified -	$\Pr(D -)$	19.75%
Correctly classified		77.96%

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

Log-Lik Intercept Only:	-206.563	Log-Lik Full Model:	-176.564
D(360):	353.128	LR(2):	59.997
		Prob > LR:	0.000
McFadden's R2:	0.145	McFadden's Adj R2:	0.131
Maximum Likelihood R2:	0.152	Cragg & Uhler's R2:	0.224
McKelvey and Zavoina's R2:	0.236	Efron's R2:	0.175
Variance of y*:	4.304	Variance of error:	3.290
Count R2:	0.780	Adj Count R2:	0.140
AIC:	0.989	AIC*n:	359.128
BIC:	-1768.857	BIC':	-48.208

```

218 .
219 . scalar SigDoseFw2 = "no"

220 . scalar MainEffwkFw2 = "bf4 age"

221 . ***** Moderator analysis for Dose=>paid employment wave two
222 . * testing potential moderators for women in wave 2
223 . set more off

224 . forvalues j = 2/2 {
      2.          sw, pr(.1):logistic HP2work age occ1w2-occ8w2 bf8 illw`j'
>   shjobw`j' havmilsq ///
>          avgcumdosew`j' ageXd2 if gender==2, coef
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.9355 >= 0.1000 removing ageXd2
p = 0.8719 >= 0.1000 removing occ4w2
p = 0.8698 >= 0.1000 removing occ7w2
p = 0.7960 >= 0.1000 removing occ3w2
p = 0.7591 >= 0.1000 removing occ8w2
p = 0.7163 >= 0.1000 removing bf8
p = 0.6916 >= 0.1000 removing shjobw2
p = 0.4726 >= 0.1000 removing havmilsq
p = 0.4933 >= 0.1000 removing occ6w2
p = 0.2614 >= 0.1000 removing occ2w2
p = 0.2755 >= 0.1000 removing occ5w2
p = 0.1676 >= 0.1000 removing avgcumdosew2

```

Logistic regression	Number of obs	=	363
	LR chi2(3)	=	48.19
	Prob > chi2	=	0.0000
Log likelihood = -182.46517	Pseudo R2	=	0.1167

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0659116	.011721	5.62	0.000	.0429388	.0888845
occlw2	-.4960407	.2867447	-1.73	0.084	-1.05805	.0659686
illw2	.2464522	.136963	1.80	0.072	-.0219903	.5148947
_cons	-4.483066	.652266	-6.87	0.000	-5.761484	-3.204648

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	23	8	31
-	70	262	332
Total	93	270	363

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	24.73%
Specificity	$\Pr(- \sim D)$	97.04%
Positive predictive value	$\Pr(D +)$	74.19%
Negative predictive value	$\Pr(\sim D -)$	78.92%
False + rate for true ~D	$\Pr(+ \sim D)$	2.96%
False - rate for true D	$\Pr(- D)$	75.27%
False + rate for classified +	$\Pr(\sim D +)$	25.81%
False - rate for classified -	$\Pr(D -)$	21.08%
Correctly classified		78.51%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      363
number of covariate patterns =    154
    Pearson chi2(150) =    156.96
        Prob > chi2 =      0.3320

```

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

Log-Lik Intercept Only:	-206.563	Log-Lik Full Model:	-182.465
D(359):	364.930	LR(3):	48.195
		Prob > LR:	0.000
McFadden's R2:	0.117	McFadden's Adj R2:	0.097
Maximum Likelihood R2:	0.124	Cragg & Uhler's R2:	0.183
McKelvey and Zavoina's R2:	0.193	Efron's R2:	0.149
Variance of y*:	4.079	Variance of error:	3.290
Count R2:	0.785	Adj Count R2:	0.161
AIC:	1.027	AIC*n:	372.930
BIC:	-1751.160	BIC':	-30.512

```

225 .
226 . * capturing significant vars
227 . local cn5: colnames(e(b))

228 . di "`cn5'"
      age occlw2 illw2 _cons

229 . local leng5 = length( "`cn5'")

230 . di `leng5'
      22

231 . local leng5b `leng5'-6

232 . di `leng5b'
      16

233 . local nuvlist5 = substr("`cn5'",1,`leng5b')

234 . di "`nuvlist5'"
      age occlw2 illw2

235 . local rhsvars5 = "`nuvlist2'"

236 . local nuvlist6= "`nuvlist2'"

```

```

237 . local nuvlist6= substr("`cn5'",1,`leng5b')
238 . di "`nuvlist6'"
      age occlw2 illw2
239 .
240 . foreach varx in `nuvlist6' {
      2. gen `varx'X`vary' = `varx'*avgcumdosew2
      3. }
241 .
242 . cap gen illw2Xd2 = illw2*avgcumdosew2
243 .
244 . sw, pr(.1): regress hp2hmcare age illw2 ageXd2 illw2Xd2 if gender==2
      begin with full model
p = 0.7203 >= 0.1000 removing illw2
p = 0.8352 >= 0.1000 removing illw2Xd2

```

Source	SS	df	MS	Number of obs =	363
Model	16.2705222	2	8.13526112	F(2, 360) =	44.59
Residual	65.6854006	360	.182459446	Prob > F =	0.0000
				R-squared =	0.1985
				Adj R-squared =	0.1941
Total	81.9559229	362	.226397577	Root MSE =	.42715

hp2hmcare	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0184548	.001962	9.41	0.000	.0145963	.0223134
ageXd2	-.0004777	.0002831	-1.69	0.092	-.0010343	.000079
_cons	-.5595097	.0984132	-5.69	0.000	-.7530467	-.3659728

```

245 .
246 .
247 . scalar SigDoseWkFw2 = "no"

```

```
248 . scalar SigDoseWkMw2 = "no"
```

```
249 . 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)

```
250 . scalar MainEffwkMw2 = "bf4 bf40"
```

```
251 . scalar MainEffwkFw2 = "age "
```

```
252 . scalar WKModMw2 = "none"
```

```
253 . scalar WkModFw2 = "none"
```

```
254 .
```

```
255 .
```

```
256 . * male sign main effects in main effects model: 2- bf4, bf40
```

```
257 . * male and female main effects model avgcumdosew2 were not signif.
```

```
258 . * male hp2wk w2 mediators: bf4 and bf40
```

```
259 . * female signif main effects in main effects model
```

```
260 .
```

```
261 . title4 "H1 pt 2 wave 2 Mediation of paid employment testing for males"
```

```
H1 pt 2 wave 2 Mediation of paid employment testing for males
```

```
262 .
```

```
263 . * male hp2wk w2 mediators: testing b4 and b40
```

```
264 .
```

```
265 . cap gen ageXillw2 = age*illw2
```

```
266 . correlate bf4 age if gender==1  
(obs=340)
```

	bf4	age
bf4	1.0000	
age	-0.4041	1.0000

```
267 .
268 . des bf4
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
269 . title4 "Possible male mediators in wave 2" "bf4 can be a male mediator in wa
> ve 2"
```

Possible male mediators in wave 2

```
270 . glm bf4 age avgcumdosew2 if gender==1, fam(gauss) link(identity)
```

Iteration 0: log likelihood = **-996.64953**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	20.7725
Deviance = 7000.331927	(1/df) Deviance	=	20.7725
Pearson = 7000.331927	(1/df) Pearson	=	20.7725

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

	<u>AIC</u>	=	5.880291
Log likelihood = -996.6495299	<u>BIC</u>	=	5035.977

bf4	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
age	-.1659274	.0203994	-8.13	0.000	-.2059095	-.1259453
avgcumdosew2	.0636104	.0995687	0.64	0.523	-.1315406	.2587614
_cons	20.59657	1.026594	20.06	0.000	18.58448	22.60866

```
271 . glm hp2work bf4 age if gender==1, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1:  deviance = 301.2605
Iteration 2:  deviance = 300.0274
Iteration 3:  deviance = 300.0164
Iteration 4:  deviance = 300.0164
Iteration 5:  deviance = 300.0164
```

```
Generalized linear models               No. of obs      =       340
Optimization      :  MQL Fisher scoring  Residual df      =       337
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 300.0163532          (1/df) Deviance =  .8902562
Pearson           = 314.8938558          (1/df) Pearson  =  .9344031
```

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

```
BIC                                     = -1664.338
```

hp2work	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.0931666	.0158695	-5.87	0.000	-.1242703	-.0620629
age	.0091277	.0069101	1.32	0.187	-.0044158	.0226712
_cons	-.2100706	.4592867	-0.46	0.647	-1.110256	.6901148

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

```
272 . title4 "bf4 can be a paid employment mediator for men"
```

```
bf4 can be a paid employment mediator for men
```

```
273 .
```

```
274 .
```

```
275 . title4 "Age can be a male mediator in wave 2"
```

```
Age can be a male mediator in wave 2
```

```
276 . glm age avgcumdosew2 if gender==1, fam(gauss) link(identity)
```

```
Iteration 0: log likelihood = -1330.6004
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853

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

Log likelihood = -1330.6004	AIC	=	7.838826
	BIC	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

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

```
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 : MQL Fisher scoring (IRLS EIM)	Residual df	=	338
	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 : $g(u) = \text{invnorm}(u)$	[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.)

278 . title4 "age could be a paid employment mediator for men in wave 2"

age could be a paid employment mediator for men in wave 2

279 .

280 . des bf4

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

281 . title4 "Age can be a male mediator in wave 2"

Age can be a male mediator in wave 2

282 . glm age bf4 avgcumdosew2 if gender==1, fam(gauss) link(identity)

Iteration 0: log likelihood = **-1300.1274**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	123.8157
Deviance = 41725.88285	(1/df) Deviance	=	123.8157
Pearson = 41725.88285	(1/df) Pearson	=	123.8157
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.665455
Log likelihood = -1300.127421	<u>BIC</u>	=	39761.53

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.9890198	.1215918	-8.13	0.000	-1.227335	-.7507042
avgcumdosew2	.5504319	.2413815	2.28	0.023	.0773329	1.023531
_cons	61.01272	1.654952	36.87	0.000	57.76907	64.25636

```
283 . glm hp2work bf4 age if gender==1, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1:  deviance = 301.2605
Iteration 2:  deviance = 300.0274
Iteration 3:  deviance = 300.0164
Iteration 4:  deviance = 300.0164
Iteration 5:  deviance = 300.0164
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	337
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 300.0163532	(1/df) Deviance	=	.8902562
Pearson	= 314.8938558	(1/df) Pearson	=	.9344031

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

```
BIC = -1664.338
```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.0931666	.0158695	-5.87	0.000	-.1242703	-.0620629
age	.0091277	.0069101	1.32	0.187	-.0044158	.0226712
_cons	-.2100706	.4592867	-0.46	0.647	-1.110256	.6901148

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

```

284 . title4 "age is not likely to be a male mediator with bf4 for paid employment
    > in wave 2"

```

```

age is not likely to be a male mediator with bf4 for paid employment in wave 2

```

```

285 .
286 .
287 .
288 . des bf4

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```

289 . title4 "bf4 is not likely to be a male paid employment mediator in wave 2"

```

```

bf4 is not likely to be a male paid employment mediator in wave 2

```

```

290 . mvreg age bf4 bf40 illw2 ageXillw2 = avgcumdosew2 if gender==1

```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
age	340	2	12.15259	0.0143	4.89591	0.0276
bf4	340	2	4.97766	0.0003	.0943548	0.7589
bf40	340	2	1.686178	0.0051	1.736932	0.1884
illw2	340	2	.5927047	0.0013	.4415312	0.5068
ageXillw2	340	2	32.91663	0.0022	.7442227	0.3889

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age						
avgcumdosew2	.5832314	.2635871	2.21	0.028	.0647536	1.101709
_cons	48.62133	.7061562	68.85	0.000	47.23231	50.01034
bf4						
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2455305	.1792032
_cons	12.52896	.2892393	43.32	0.000	11.96002	13.0979
bf40						
avgcumdosew2	.0482004	.0365729	1.32	0.188	-.0237387	.1201394
_cons	2.097753	.0979795	21.41	0.000	1.905026	2.290479
illw2						
avgcumdosew2	.0085423	.0128556	0.66	0.507	-.0167449	.0338294
_cons	.2741359	.0344406	7.96	0.000	.206391	.3418808

ageXillw2						
avgcumdosew2	.6159172	.7139551	0.86	0.389	-.7884376	2.020272
_cons	14.92518	1.912703	7.80	0.000	11.16288	18.68748

```

291 . glm hp2work bf40 ageXillw2 age illw2 if gender==1, fam(binomial) link(probit
> ) ///
>      irls scale(dev)

```

```

Iteration 1:  deviance = 308.9955
Iteration 2:  deviance = 308.2796
Iteration 3:  deviance = 308.2778
Iteration 4:  deviance = 308.2778
Iteration 5:  deviance = 308.2778

```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	335
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 308.2777886	(1/df) Deviance	=	.9202322
Pearson	= 335.9124972	(1/df) Pearson	=	1.002724

Variance function: V(u) = u*(1-u)	[Bernoulli]
Link function : g(u) = invnorm(u)	[Probit]
	BIC = -1644.419

hp2work	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf40	.1968555	.0501932	3.92	0.000	.0984787	.2952324
ageXillw2	.0233836	.0127678	1.83	0.067	-.0016408	.048408
age	.0063243	.0075384	0.84	0.402	-.0084507	.0210993
illw2	-1.134791	.6961081	-1.63	0.103	-2.499138	.2295553
_cons	-1.667851	.3743004	-4.46	0.000	-2.401466	-.9342355

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

```

292 . title4 "only age is a possible mediator for men when b4 b40 and age are toge
    > ther"

```

```

only age is a possible mediator for men when b4 b40 and age are together

```

```

293 .

```

```

294 .

```

```

295 . title4 "interaction of ageXillw2 impacts paid employment as male mediator an
    > d moderator"

```

```

interaction of ageXillw2 impacts paid employment as male mediator and moderato
> r

```

```

296 . glm ageXillw2 illw2 age avgcumdosew2 if gender==1, fam(gaussian) link(identi
    > ty)

```

```

Iteration 0:   log likelihood = -1109.6595

```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	336
		Scale parameter	=	40.5026
Deviance	= 13608.87389	(1/df) Deviance	=	40.5026
Pearson	= 13608.87389	(1/df) Pearson	=	40.5026

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

		<u>AIC</u>	=	6.550938
Log likelihood	= -1109.659496	<u>BIC</u>	=	11650.35

ageXillw2	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw2	53.11213	.5991873	88.64	0.000	51.93774	54.28651
age	.2512225	.0292235	8.60	0.000	.1939455	.3084996
avgcumdosew2	.0156969	.1390398	0.11	0.910	-.2568161	.2882098
_cons	-11.84953	1.441655	-8.22	0.000	-14.67513	-9.023941

```

297 . glm hp2work ageXillw2 age illw2 avgcumdosew2 if gender==1, fam(binomial) irl
> s ///
>     scale(dev) link(probit)

```

```

Iteration 1:   deviance =  322.7831
Iteration 2:   deviance =  322.5045
Iteration 3:   deviance =  322.5038
Iteration 4:   deviance =  322.5038
Iteration 5:   deviance =  322.5038

```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	335
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 322.5038421	(1/df) Deviance	=	.962698
Pearson	= 337.2279798	(1/df) Pearson	=	1.006651

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

BIC = -1630.193

hp2work	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
ageXillw2	.0278044	.0129945	2.14	0.032	.0023357	.0532732
age	.0127618	.0073249	1.74	0.081	-.0015948	.0271183
illw2	-1.215538	.7144847	-1.70	0.089	-2.615902	.1848265
avgcumdosew2	.0031971	.02854	0.11	0.911	-.0527403	.0591346
_cons	-1.579985	.3683777	-4.29	0.000	-2.301992	-.8579781

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

```

298 .
299 . scalar WkMedMw2 = "age ageXillw2"

300 . * moderate negative correlation between bf4 and age generates ///
> *     annihilation of effect among men in wave 2"

```

```

301 .
302 .
303 . title4 "Testing possible female paid employment mediators for paid employmen
> t in wave 2"

```

```

Testing possible female paid employment mediators for paid employment in wave
> 2

```

```

304 .
305 . title4 "Test of age as possible female mediator in wave 2"

```

```

Test of age as possible female mediator in wave 2

```

```

306 . glm age avgcumdosew2 if gender==2, fam(gauss) link(identity)

```

```

Iteration 0: log likelihood = -1406.9403

```

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

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

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

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

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

```
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.)

```
308 . title4 "age can be a wave 2 mediator for women with hp2work "
```

```
age can be a wave 2 mediator for women with hp2work
```

```
309 .
```

```
310 .
```

```
311 . title4 "Test of b40 as female mediator of paid employment in wave 2"
```

```
Test of b40 as female mediator of paid employment in wave 2
```

```
312 . glm bf40 age avgcumdosew2 if gender==2, fam(gauss) link(identity)
```

```
Iteration 0: log likelihood = -812.90018
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	360
	Scale parameter	=	5.202871
Deviance = 1873.033605	(1/df) Deviance	=	5.202871
Pearson = 1873.033605	(1/df) Pearson	=	5.202871

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

	<u>AIC</u>	=	4.495318
Log likelihood = -812.900181	<u>BIC</u>	=	-248.9514

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0344949	.0102598	3.36	0.001	.0143862	.0546037
avgcumdosew2	.1276677	.0881819	1.45	0.148	-.0451657	.3005011
_cons	1.318795	.5213154	2.53	0.011	.2970355	2.340554

```
313 . glm hp2work bf40 age if gender==2, fam(binomial) link(probit) irls scale(de
> v)
```

```
Iteration 1: deviance = 370.0322
Iteration 2: deviance = 369.4792
Iteration 3: deviance = 369.4783
Iteration 4: deviance = 369.4783
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 369.4782806	(1/df) Deviance	=	1.026329
Pearson = 367.3661843	(1/df) Pearson	=	1.020462

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

	BIC	=	-1752.507
--	-----	---	-----------

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.0541122	.0322636	1.68	0.094	-.0091233	.1173476
age	.0384233	.0067268	5.71	0.000	.025239	.0516076
_cons	-2.8289	.3651989	-7.75	0.000	-3.544677	-2.113123

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

314 . title4 "b40 with age is not likely to be a wv 2 mediator for women"

b40 with age is not likely to be a wv 2 mediator for women

315 .

316 .

317 . title4 "bf40 Test of female mediation of paid employment in wave 2"

bf40 Test of female mediation of paid employment in wave 2

318 . glm bf40 avgcumdosew2 if gender==2, fam(gauss) link(identity)

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

Generalized linear models

Optimization : **ML**

Deviance = **1931.847477**

Pearson = **1931.847477**

No. of obs = **363**

Residual df = **361**

Scale parameter = **5.351378**

(1/df) Deviance = **5.351378**

(1/df) Pearson = **5.351378**

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

[**Gaussian**]

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

[**Identity**]

Log likelihood = **-818.5116931**

AIC = **4.520726**

BIC = **-196.0319**

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

```
319 . glm hp2work bf40 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1:  deviance = 406.4865
Iteration 2:  deviance = 406.0549
Iteration 3:  deviance = 406.0547
Iteration 4:  deviance = 406.0547
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  MQL Fisher scoring                 Residual df     =       361
                  (IRLS EIM)                          Scale parameter =         1
Deviance          = 406.0547444                        (1/df) Deviance = 1.124805
Pearson           = 360.1809662                        (1/df) Pearson  = .9977312
```

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

```
BIC = -1721.825
```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.080565	.0316866	2.54	0.011	.0184603	.1426696
_cons	-.921639	.1303745	-7.07	0.000	-1.177168	-.6661097

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

```
320 . title4 "bf40 alone is a mediator for women"
```

```
bf40 alone is a mediator for women
```

```
321 .
```

```
322 .
```

```
323 . title "bf4 Test of female mediation of paid employment in wave 2"
```

```
*****
> *
*****
> *
*****
> *
*****      bf4 Test of female mediation of paid employment in wave 2      *****
> *
*****
> *
```

```

*****
> *
*****
17 Jun 2012    10:04:59    ****
> *
*****
> *
*****
> *

```

```
324 . glm bf4 avgcumdosew2 if gender==2, fam(gauss) link(identity)
```

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

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

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

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

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

```
325 . glm hp2work bf4 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```

Iteration 1:    deviance = 370.9717
Iteration 2:    deviance = 370.7179
Iteration 3:    deviance = 370.7176
Iteration 4:    deviance = 370.7176

```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 370.7176349	(1/df) Deviance	=	1.026919
Pearson = 356.8979308	(1/df) Pearson	=	.9886369

[Bernoulli]
[Probit]

BIC = -1757.162

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.090794	.0144985	-6.26	0.000	-.1192106	-.0623775
_cons	.2257867	.1560342	1.45	0.148	-.0800347	.531608

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

326 . title4 "bf4 alone is a mediator for women"

bf4 alone is a mediator for women

327 .

328 .

329 .

```
330 . title "Test of female mediation of paid employment in wave 2"
```

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
*****  
Test of female mediation of paid employment in wave 2  
> *  
*****  
> *  
*****  
> *  
*****  
17 Jun 2012    10:05:02 *****  
> *  
*****  
> *
```

```
331 . glm illw2 avgcumdosew2 if gender==2, fam(gauss) link(identity)
```

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

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

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

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

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

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

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

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

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

	BIC	=	-1722.571
--	-----	---	-----------


```
339 . mvreg bf4 age bf40 = avgcumdosew2 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.151001	0.0249	9.209323	0.0026
age	363	2	11.70121	0.0306	11.37694	0.0008
bf40	363	2	2.313305	0.0114	4.155047	0.0422

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew2	-.595012	.1960703	-3.03	0.003	-.9805954	-.2094285
_cons	11.02048	.3223763	34.19	0.000	10.38651	11.65445
age						
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6264181	2.378231
_cons	48.86944	.7323225	66.73	0.000	47.42929	50.3096
bf40						
avgcumdosew2	.1794903	.0880548	2.04	0.042	.0063255	.3526551
_cons	3.004543	.1447786	20.75	0.000	2.719828	3.289259

```
340 . glm hp2work bf4 age bf40 if gender==2, fam(binomial) link(probit) irls ///
> scale(dev)
```

```
Iteration 1: deviance = 354.2404
Iteration 2: deviance = 353.2021
Iteration 3: deviance = 353.1978
Iteration 4: deviance = 353.1978
Iteration 5: deviance = 353.1978
```

```
Generalized linear models
Optimization      : MQL Fisher scoring
                   (IRLS EIM)
Deviance          = 353.1977844
Pearson           = 373.3187421
```

```
No. of obs       = 363
Residual df      = 359
Scale parameter   = 1
(1/df) Deviance  = .9838378
(1/df) Pearson   = 1.039885
```

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

```
[Bernoulli]
[Probit]
```

```
BIC = -1762.893
```



```
347 . mvreg bf4 age bf40 illw2 = avgcumdosew2 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.151001	0.0249	9.209323	0.0026
age	363	2	11.70121	0.0306	11.37694	0.0008
bf40	363	2	2.313305	0.0114	4.155047	0.0422
illw2	363	2	.8699891	0.0380	14.24594	0.0002

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew2	-.595012	.1960703	-3.03	0.003	-.9805954	-.2094285
_cons	11.02048	.3223763	34.19	0.000	10.38651	11.65445
age						
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6264181	2.378231
_cons	48.86944	.7323225	66.73	0.000	47.42929	50.3096
bf40						
avgcumdosew2	.1794903	.0880548	2.04	0.042	.0063255	.3526551
_cons	3.004543	.1447786	20.75	0.000	2.719828	3.289259
illw2						
avgcumdosew2	.1249912	.0331157	3.77	0.000	.0598673	.1901152
_cons	.301285	.0544484	5.53	0.000	.1942091	.4083609

```
348 . glm hp2work bf4 age bf40 illw2 if gender==2, fam(binomial) ///
> link(probit) irls scale(dev)
```

```
Iteration 1: deviance = 353.9708
Iteration 2: deviance = 352.9328
Iteration 3: deviance = 352.9282
Iteration 4: deviance = 352.9282
Iteration 5: deviance = 352.9282
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	358
(IRLS EIM)	Scale parameter	=	1
Deviance = 352.928242	(1/df) Deviance	=	.9858331
Pearson = 374.7035801	(1/df) Pearson	=	1.046658

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

```
BIC = -1757.268
```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.0619013	.0162545	-3.81	0.000	-.0937595	-.0300431
age	.0281218	.0070538	3.99	0.000	.0142966	.0419469
bf40	.0270841	.0335369	0.81	0.419	-.038647	.0928153
illw2	.0420195	.0835799	0.50	0.615	-.1217941	.2058332
_cons	-1.624207	.4693912	-3.46	0.001	-2.544197	-.7042168

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

```

349 . qui: {
      When all are together only age and b4 are a wave 2 mediators for women

350 .
351 .
352 . scalar wkMedMw2 = "age bf4"

353 .
354 . scalar SigDoseWkMw2 = "no"

355 . scalar MainEffwkMw2 = "age"

356 . scalar MainEffwkFw2 = "age"

357 . scalar wkMedFw2 = "age b4"

358 .
359 .
360 . title4 "*---1.- Summary matrix construction Paid employment partition: first
      > two rows"

```

```

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

```

```

361 .

```

```

362 .      matrix define wkMw2 = J(1,8, 0)

363 .      matrix define  wkFw2 = J(1,8, 0)

364 . matrix colnames  wkMw2=  hypnum ptnum wave gender medsig numMA sig numModsig
    > numMed

365 . matrix colnames  wkFw2=  hypnum ptnum wave gender medsig numMA sig numModsig
    > numMed

366 .      matrix rownames  wkMw2 = workMw2

367 .      matrix rownames  wkFw2 = workFw2

368 .      matrix define  wkMw2= (1, 2, 2, 1, 0 ,2,  0  , 2 )

369 .      matrix define  wkFw2= (1, 2, 2, 2, 0, 1,  0  , 2 )

370 .

371 .      matrix define H1pt2w2 = ( wkMw2 \  wkFw2)

372 .      matrix colnames H1pt2w2 =  hypnum ptnum wave  medsig numMA sig numModsig
    > numMed

373 .      matrix rownames H1pt2w2 =  wkMw2 wkFw2

374 .      matlist H1pt2w2

```

		hypnum	ptnum	wave	medsig	numMA sig	numModsi
> g	numMed	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2	0	2					
	wkFw2	1	2	2	2	0	
> 1	0	2					

```

375 .
376 .
377 . scalar list
    MainEffwkFw2 = age
    MainEffwkMw2 = age
    inthobMedMw2 = age
        inthobMw2 = age
    sxlifeMedMw2 = age illw2
    SigDoseSxlifeFw2 = no
    MainEffsxlifeFw2 = age radhlw2 bf4 bf4m
    PrbfmhmModMw2 = none
    MainEffProbSocFw2 = age radhlw2 avgcumdosew2 bf4
    MainEffPrbsocMw2 = age radhlw2 shjobw2
    MainEffhmcrFw2 = age
    hmcrMedFw2 = age bf4
    hmcrModMw2 = none
    MainEffhmcrMw2 = age
        wkMedFw2 = age b4
        wkMedMw2 = age bf4
    MainEffVactnMw2 = age radhlw2
    MainEffsxlifeMw2 = age bf4 bf40 shjobw2 shrelaw2 radhlw2
    MainEffPrbfmhmMw2 = bf4 bf6 bf7
    ProbsocMedFw2 = age bf4 radhlw2
    hmcareMedFw2 = age bf4
        WkhmcrMw2 = age b4
    MainEffhmcrw2 = age
    hmcrModFw2 = none
    SigDoseHmcrFw2 = yes
    NumhmcrModMw2 = none
    SigDosehmcrMw2 = no
    SigdosehmcrFw2 = yes
    hmcrMedMw2 = age ageXillw2
    SigDosehmcrFw2 = no
    MainEffhmcareMw2 = age
        WkMedMw2 = age ageXillw2
        wkMedFw3 = radhlw3 age ageXillw3 bf40 bf4m bf1
    VactnMedFw2 = age illw2 radhlw2
    VactnMedMw2 = age illw2
    VacatnModFw2 = none
    MainEffVactnFw2 = age radhlw2 bf7m
    SigDoseVactnFw2 = no
    VactnModMw2 = none
    vactnModMw2 = none
    SigDoseVactnMw2 = no
    inthobMedFw2 = age bf4 illw2 bf4m
    InthbModFw2 = none
    MainEffInthbFw2 = age radhlw2 bf4
    SigdoseInthbFw2 = no
    InthbModMw2 = none

```

```

MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
MainEffMw2 = radhlw2 bf4 bf40
SigdoseMEinthob = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
SxLifeModFw2 = no
sxlifeModFw2 = none
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf4 bf6 bf7
ProbsocMedMw2 = age
ProbsocModFw2 = none
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
PrbsocModMw2 = none
SigdoseMw2 = none
hmcareMedMw2 = age
hmcareModFw2 = none
MainEffhmcarew2 = age
SigdoseHmcareFw2 = no
hmcareModMw2 = none
SigDoseHmcareMw2 = no
NameMedMw2 = age ageXillw2
  NumModMw2 = none
SigDosehmcareMw2 = no
SigDoseWKMw2 = no
  WkMedFw2 = age bf4
  WkModFw2 = none
  WKModMw2 = none
SigDoseWkMw2 = no
SigDoseWkFw2 = no
SigDoseFw2 = no
  wkModFw2 = none
  wkModMw2 = none
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
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no

```

```

378 . * moderator construction
379 . * none used because basic dose work relationship washes out
380 .
381 . title "2. Hyp 1 pt 2 wave 2 male dose Hp2hmcare impact explored"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****      2. Hyp 1 pt 2 wave 2 male dose Hp2hmcare impact explored      *****
> *
*****
> *
*****
> *
*****
> *
*****      17 Jun 2012      10:05:10      *****
> *
*****
> *
*****
> *

```

```

382 .
383 . * ----- testing male and female moderators-wave 2 for hmcare-----
> ----
384 .
385 . cap gen hp2hmcare=HP2hmcare
386 .

```

```

387 . forvalues j = 2/2 {
      2. set more off
      3. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      4. di as input "For females hp2hmcare on Wave 2 with dose ns"
      5.      des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' bf8 /
> //
>      marrw`j'1-marrw`j'6 `w2bf' radhlw`j'
      6.      sw, pr(.1): logistic hp2hmcare marrw`j'3-marrw`j'6 age havmilsq
> ///
>      avgcumdosew1 bf8 illw`j' shjobw`j' suprtw`j' if gender==1, c
> oef
      7.      estat gof
      8.      estat class
      9.      fitstat
     10.      }
For females hp2hmcare on Wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
incl1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single

```

marrw22      byte    %8.0g      marrw2==2. cohabitating
marrw23      byte    %8.0g      marrw2==3. married
marrw24      byte    %8.0g      marrw2==4. separated
marrw25      byte    %8.0g      marrw2==5. divorced
marrw26      byte    %8.0g      marrw2==6. widowed
bf1          float   %9.0g      bf1 = max(0, kzchorn - 40)
bf4          float   %9.0g      bf4 = max(0, 24 - BSIsoma)
bf6          float   %9.0g      bf6= max(0, radtlw2 - 10)
bf7          float   %9.0g      bf7= max(0, 10 - radtlw2)
bf14         float   %9.0g      bf14= max(0, radw2 - 10) * bf12
bf15         float   %9.0g      bf15= max(0, 10 - radw2) * bf12
bf40         float   %9.0g      bf40 = max(0, icdxcnt -
                                1.01635E-007)
radhlw2      double  %8.0g      how much believed personal
                                health is affected by
                                radiation in 1996

```

```

                                begin with full model
p = 0.7326 >= 0.1000 removing marrw25
p = 0.6899 >= 0.1000 removing avgcumdosew1
p = 0.5598 >= 0.1000 removing marrw24
p = 0.5279 >= 0.1000 removing havmilsq
p = 0.4308 >= 0.1000 removing suprtw2
p = 0.3812 >= 0.1000 removing bf8
p = 0.3963 >= 0.1000 removing marrw26
p = 0.1763 >= 0.1000 removing shjobw2
p = 0.2257 >= 0.1000 removing marrw23

```

Logistic regression

```

Number of obs    =      340
LR chi2(2)       =      28.54
Prob > chi2      =      0.0000
Pseudo R2       =      0.0826

```

Log likelihood = **-158.60117**

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0538093	.0119121	4.52	0.000	.030462	.0771566
illw2	.347449	.2097345	1.66	0.098	-.063623	.7585211
_cons	-4.244759	.6492495	-6.54	0.000	-5.517264	-2.972253

Logistic model for hp2hmcare, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =      91
Pearson chi2(88) =      90.18
Prob > chi2 =      0.4155

```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	3	2	5
-	67	268	335
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	4.29%
Specificity	$\Pr(- \sim D)$	99.26%
Positive predictive value	$\Pr(D +)$	60.00%
Negative predictive value	$\Pr(\sim D -)$	80.00%
False + rate for true ~D	$\Pr(+ \sim D)$	0.74%
False - rate for true D	$\Pr(- D)$	95.71%
False + rate for classified +	$\Pr(\sim D +)$	40.00%
False - rate for classified -	$\Pr(D -)$	20.00%
Correctly classified		79.71%

Measures of Fit for **logistic** of hp2hmcare

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-158.601
D(337):	317.202	LR(2):	28.543
		Prob > LR:	0.000
McFadden's R2:	0.083	McFadden's Adj R2:	0.065
Maximum Likelihood R2:	0.081	Cragg & Uhler's R2:	0.126
McKelvey and Zavoina's R2:	0.140	Efron's R2:	0.094
Variance of y*:	3.826	Variance of error:	3.290
Count R2:	0.797	Adj Count R2:	0.014
AIC:	0.951	AIC*n:	323.202
BIC:	-1647.152	BIC':	-16.886

```

388 .
389 . scalar SigDosehmcrMw2 = "no"

390 . scalar MainEffhmcrMw2 = "age"

391 . scalar hmcrModMw2 = "none"

392 .
393 .
394 .
395 . title4 "Trimmed female Hp2hmcare moderator model"

```

```

Trimmed female Hp2hmcare moderator model

```

```

396 .
397 . cap gen ageXd2= age*avgcumdosew2

398 .
399 . forvalues j = 2/2 {
      2. set more off
      3. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      4. di as input "For females HP2hmcare on Wave 2 with dose ns"
      5.         des age avgcumdosew`j' ///
>         marrw`j'1-marrw`j'6 `w2bf' radhlw`j'
      6.         sw, pr(.1): logistic hp2hmcare marrw`j'3-marrw`j'6 age havmilsq
> ///
>         avgcumdosew1 illw`j' ageXd2 if gender==2, coef
      7.         estat gof
      8.         estat class
      9.         fitstat
     10.         }
For females HP2hmcare on Wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf6	float	%9.0g		bf6= max(0, radtlw2 - 10)

```

bf7          float   %9.0g          bf7= max(0, 10 - radtlw2)
bf14         float   %9.0g          bf14= max(0, radw2 - 10) * bf12
bf15         float   %9.0g          bf15= max(0, 10 - radw2) * bf12
bf40         float   %9.0g          bf40 = max(0, icdxcnt -
                                     1.01635E-007)
radhlw2      double  %8.0g          how much believed personal
                                     health is affected by
                                     radiation in 1996

```

```

note: marrw24 dropped because of estimability
note: o.marrw24 dropped because of estimability
note: 1 obs. dropped because of estimability

```

```

begin with full model
p = 0.9652 >= 0.1000 removing ageXd2
p = 0.9353 >= 0.1000 removing illw2
p = 0.8323 >= 0.1000 removing marrw26
p = 0.6372 >= 0.1000 removing marrw25
p = 0.4227 >= 0.1000 removing havmilsq
p = 0.1231 >= 0.1000 removing avgcumdosew1

```

```

Logistic regression                                Number of obs   =       362
                                                    LR chi2(2)      =       80.23
                                                    Prob > chi2     =       0.0000
Log likelihood = -192.54484                      Pseudo R2      =       0.1724

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
marrw23	.8360757	.3218733	2.60	0.009	.2052155	1.466936
age	.0882987	.0122238	7.22	0.000	.0643404	.112257
_cons	-5.890481	.7226602	-8.15	0.000	-7.306869	-4.474093

Logistic model for hp2hmcare, goodness-of-fit test

```

number of observations =       362
number of covariate patterns =       86
Pearson chi2(83) =       87.28
Prob > chi2 =       0.3526

```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	60	30	90
-	64	208	272
Total	124	238	362

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

True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	48.39%
Specificity	$\Pr(- \sim D)$	87.39%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	76.47%
False + rate for true ~D	$\Pr(+ \sim D)$	12.61%
False - rate for true D	$\Pr(- D)$	51.61%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	23.53%
Correctly classified		74.03%

Measures of Fit for **logistic** of **hp2hmcare**

Log-Lik Intercept Only:	-232.660	Log-Lik Full Model:	-192.545
D(359):	385.090	LR(2):	80.230
		Prob > LR:	0.000
McFadden's R2:	0.172	McFadden's Adj R2:	0.160
Maximum Likelihood R2:	0.199	Cragg & Uhler's R2:	0.275
McKelvey and Zavoina's R2:	0.301	Efron's R2:	0.213
Variance of y*:	4.706	Variance of error:	3.290
Count R2:	0.740	Adj Count R2:	0.242
AIC:	1.080	AIC*n:	391.090
BIC:	-1730.011	BIC':	-68.447

```

400 .
401 . qui {

```

Caveat: We drop bf8 because it is dependent on a variable in a future wave.

If it depended on a past wave variable we might have kept it.

But when it is dependent on something that has not happened yet,

it is too latent to consider in a wave specific analysis.

```

402 . des bf8 bf5m bf4m

```

variable name	storage type	display format	value label	variable label
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```

403 . scalar SigDosehmcrFw2 = "no"

```

```

404 . scalar MainEffhmcrFw2 = "marrw23 age"

```

```

405 .

```

```

406 .

```

```

407 . title4 "home care wave 2 male mediator analysis"

```

home care wave 2 male mediator analysis

```

408 .
409 . title4 "age is a possible male mediator of home care in wave 2"

```

```

age is a possible male mediator of home care in wave 2

```

```

410 . glm age avgcumdosew2 if gender==1, fam(gaussian) link(identity)

```

```

Iteration 0:   log likelihood = -1330.6004

```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853

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

	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```

411 . 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 : MQL 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 : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-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.)

```

412 .
413 . scalar hmcrMedMw2 = "age ageXillw2"

414 .
415 . di as input "age is a possible male mediator for home care in wave 2"
    age is a possible male mediator for home care in wave 2

416 .
417 .
418 . di as input "age and illw2 as main effects together suppress illw2"
    age and illw2 as main effects together suppress illw2

419 . glm illw2 age avgcumdosew2 if gender==1, family(gaussian) link(identity)

```

Iteration 0: log likelihood = **-294.89214**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	.3347555
Deviance = 112.812617	(1/df) Deviance	=	.3347555
Pearson = 112.812617	(1/df) Pearson	=	.3347555

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

	<u>AIC</u>	=	1.752307
Log likelihood = -294.8921379	<u>BIC</u>	=	-1851.542

illw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.010896	.0025896	4.21	0.000	.0058205	.0159716
avgcumdosew2	.0021874	.0126399	0.17	0.863	-.0225863	.0269611
_cons	-.2556434	.1303222	-1.96	0.050	-.5110702	-.0002165

```
420 . glm hp2hmcare illw2 age if gender==1, family(binomial) irls scale(dev) link
> (probit)
```

```
Iteration 1: deviance = 318.4593
Iteration 2: deviance = 317.6467
Iteration 3: deviance = 317.6458
Iteration 4: deviance = 317.6458
```

```
Generalized linear models                               No. of obs      =       340
Optimization      : ML Fisher scoring                 Residual df     =       337
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 317.6458464                        (1/df) Deviance =  .9425693
Pearson           = 345.1774401                        (1/df) Pearson  =  1.024265
```

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

```
BIC = -1646.709
```

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
illw2	.1994222	.1221622	1.63	0.103	-.0400114	.4388557
age	.0303611	.0065398	4.64	0.000	.0175433	.043179
_cons	-2.436578	.3445976	-7.07	0.000	-3.111977	-1.761179

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

```
421 .
422 .
423 . di as input "Interaction of age and wave 2 illness for males is mediator-mod
> erator on hmcare"
Interaction of age and wave 2 illness for males is mediator-moderator on hmcar
> e
424 .
```

```
425 . cap gen ageXillw2 = age*illw2
```

```
426 . glm illw2 avgcumdosew2 if gender==1, family(gaussian) link(identity)
```

```
Iteration 0: log likelihood = -303.59609
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988
Variance function: $V(u) = 1$	[Gaussian]		
Link function : $g(u) = u$	[Identity]		
	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.0085423	.0128556	0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406	7.96	0.000	.2066336	.3416382

```
427 . glm hp2hmcare illw2 avgcumdosew2 ageXillw2 if gender==1, family(binomial) //
> /
> irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 325.2943
Iteration 2: deviance = 325.0754
Iteration 3: deviance = 325.0739
Iteration 4: deviance = 325.0739
Iteration 5: deviance = 325.0739
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 325.0738987	(1/df) Deviance	=	.9674818
Pearson = 337.8592784	(1/df) Pearson	=	1.005534
Variance function: $V(u) = u*(1-u)$	[Bernoulli]		
Link function : $g(u) = \text{invnorm}(u)$	[Probit]		
	BIC	=	-1633.452

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	-2.019327	.7153941	-2.82	0.005	-3.421474	-.6171808
avgcumdosew2	-.000217	.0298223	-0.01	0.994	-.0586676	.0582336
ageXillw2	.0422954	.0126323	3.35	0.001	.0175365	.0670543
_cons	-.9410134	.0916093	-10.27	0.000	-1.120564	-.7614625

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

```

428 .
429 .
430 .
431 . * Saving mediators as scalars for Dose=work relationship
432 . **** female mediators of dose-paid employment: radhlw2, age, bf40, bf4m, bf4
    > , bf1
433 .
434 . scalar hmcrMedMw2 = "age ageXillw2"

435 . scalar hmcrMedFw2 = "radhlw2 age bf40 bf4m bf4 bf1"

436 .
437 .
438 .
439 . cap gen hp2vacatn = HP2vacatn

440 .
441 .
442 . title "2. H1 pt2 wave 2 Dose female moderator Homecare impact "
```

```

*****
> *
*****
> *
***** ****
> *
***** ****
> *
***** 2. H1 pt2 wave 2 Dose female moderator Homecare impact ****
> *
***** ****
> *
***** ****
> *
***** 17 Jun 2012 10:05:43 ****
> *
*****
```

```

> *
*****
> *

443 .
444 .
445 . * review of general model for men and women
446 .
447 . forvalues j = 2/2 {
      2. set more off
      3.
448 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
449 . foreach var in HP2hmcare {
      5.
450 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      6. title "chunk 3 H1 test pt 2 :Gender= `k' model Wave = `j' for `e(de
      > pvar)' "
      7. di _skip(4)
      8.
451 .
452 . 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' radhlw2 ///
      > illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
      > chrw`j' ///
      > havmilsq if gender==2, coef difficult iterate(50)
      9. estat class
      10. estat gof
      11. fitstat
      12.
453 . }
      13. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

occ5w2	-4.352791	1.883178	-2.31	0.021	-8.043752	-.6618289
occ6w2	-5.059677	2.021732	-2.50	0.012	-9.022199	-1.097155
occ7w2	-1.364295	1.545156	-0.88	0.377	-4.392746	1.664156
occ8w2	-.5789576	1.792303	-0.32	0.747	-4.091808	2.933892
marrw21	-.0690078	1.129464	-0.06	0.951	-2.282717	2.144702
marrw22	.7043443	1.44356	0.49	0.626	-2.124982	3.533671
marrw23	2.097285	.8281102	2.53	0.011	.4742186	3.720351
marrw25	.9609574	1.20757	0.80	0.426	-1.405836	3.327751
marrw26	0	(omitted)				
inclw2	2.105274	1.594442	1.32	0.187	-1.019775	5.230323
inc2w2	3.407471	1.542788	2.21	0.027	.3836621	6.43128
inc3w2	2.870172	1.549672	1.85	0.064	-.1671285	5.907473
inc4w2	3.606463	1.894634	1.90	0.057	-.1069505	7.319876
radhlw2	-.0068123	.0061828	-1.10	0.271	-.0189302	.0053057
havmil	.0011484	.0030211	0.38	0.704	-.0047728	.0070696
avgcumdosew2	-.2667926	.1232968	-2.16	0.030	-.5084499	-.0251353
bf1	-.0183931	.0079003	-2.33	0.020	-.0338774	-.0029088
bf4	-.2337773	.0416245	-5.62	0.000	-.3153598	-.1521948
bf6	.0040038	.0067939	0.59	0.556	-.009312	.0173196
bf7	-.126659	.0709704	-1.78	0.074	-.2657584	.0124404
bf14	-.0000228	.0000659	-0.35	0.729	-.0001521	.0001064
bf15	0	(omitted)				
bf40	.0786288	.0758899	1.04	0.300	-.0701127	.2273704
deaw2	.6463714	.2506264	2.58	0.010	.1551526	1.13759
dvcew2	1.46465	1.066188	1.37	0.170	-.6250398	3.554339
sepaw2	-1.747364	1.628008	-1.07	0.283	-4.938201	1.443472
accdw2	-.6760904	.5387942	-1.25	0.210	-1.732108	.3799268
movew2	-.5261615	.493185	-1.07	0.286	-1.492786	.4404633
radhlw2	0	(omitted)				
illw2	-.1619986	.1844507	-0.88	0.380	-.5235154	.1995182
shfamw2	-.0039886	.0060041	-0.66	0.506	-.0157565	.0077793
shhlw2	-.0091905	.0062486	-1.47	0.141	-.0214375	.0030565
shjobw2	.0003458	.0057176	0.06	0.952	-.0108605	.011552
shrelaw2	-.0091776	.006756	-1.36	0.174	-.0224192	.0040639
suprtw2	-.0077623	.0046946	-1.65	0.098	-.0169635	.0014389
suchrw2	.0040413	.0050755	0.80	0.426	-.0059065	.013989
havmilsq	-1.23e-06	2.83e-06	-0.44	0.664	-6.79e-06	4.32e-06
_cons	12.31935	1273.659	0.01	0.992	-2484.005	2508.644

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	85	27	112
-	39	211	250
Total	124	238	362

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

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	68.55%
Specificity	$\Pr(- \sim D)$	88.66%
Positive predictive value	$\Pr(D +)$	75.89%
Negative predictive value	$\Pr(\sim D -)$	84.40%
False + rate for true ~D	$\Pr(+ \sim D)$	11.34%
False - rate for true D	$\Pr(- D)$	31.45%
False + rate for classified +	$\Pr(\sim D +)$	24.11%
False - rate for classified -	$\Pr(D -)$	15.60%
Correctly classified		81.77%

Logistic model for HP2hmcare, goodness-of-fit test

```

      number of observations =      362
number of covariate patterns =      362
      Pearson chi2(316) =      339.77
              Prob > chi2 =      0.1713

```

Measures of Fit for **logistic** of HP2hmcare

Log-Lik Intercept Only:	-232.660	Log-Lik Full Model:	-144.488
D(312):	288.975	LR(45):	176.345
		Prob > LR:	0.000
McFadden's R2:	0.379	McFadden's Adj R2:	0.164
Maximum Likelihood R2:	0.386	Cragg & Uhler's R2:	0.533
McKelvey and Zavoina's R2:	0.660	Efron's R2:	0.429
Variance of y*:	9.672	Variance of error:	3.290
Count R2:	0.818	Adj Count R2:	0.468
AIC:	1.075	AIC*n:	388.975
BIC:	-1549.218	BIC':	88.779

```

454 .
455 . title4 "Partly trimmed Female Main effects model for dose=> homecare Wave 2"
>

```

Partly trimmed Female Main effects model for dose=> homecare Wave 2

```

456 .   logit hp2hmcare age radhlw2 occ1w2-occ8w2 inclw2-inc4w2 ///
>       avgcumdosew2 bf4 bf7 deaw2 if gender==2

```

```

Iteration 0:   log likelihood = -233.72859
Iteration 1:   log likelihood = -172.25111
Iteration 2:   log likelihood = -169.51991
Iteration 3:   log likelihood = -169.49972
Iteration 4:   log likelihood = -169.49971

```

```

Logistic regression                                Number of obs   =          363
                                                    LR chi2(18)    =         128.46
                                                    Prob > chi2    =          0.0000
Log likelihood = -169.49971                      Pseudo R2      =          0.2748

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.079561	.0142687	5.58	0.000	.0515948	.1075272
radhlw2	-.0083952	.0044827	-1.87	0.061	-.0171812	.0003907
occ1w2	-2.32278	1.311607	-1.77	0.077	-4.893483	.2479237
occ2w2	-1.88582	1.338008	-1.41	0.159	-4.508267	.7366266
occ3w2	-1.509669	1.335746	-1.13	0.258	-4.127683	1.108345
occ4w2	-2.168722	1.418902	-1.53	0.126	-4.949719	.6122755
occ5w2	-3.544379	1.583073	-2.24	0.025	-6.647145	-.4416134
occ6w2	-3.825132	1.799878	-2.13	0.034	-7.352828	-.2974366
occ7w2	-1.495633	1.343599	-1.11	0.266	-4.12904	1.137773
occ8w2	-1.841158	1.495976	-1.23	0.218	-4.773218	1.090901
inclw2	1.974091	1.375803	1.43	0.151	-.7224332	4.670615
inc2w2	2.865688	1.343638	2.13	0.033	.2322063	5.499169
inc3w2	2.529133	1.351328	1.87	0.061	-.1194215	5.177687
inc4w2	2.74918	1.595275	1.72	0.085	-.3775016	5.875861
avgcumdosew2	-.2305613	.0983157	-2.35	0.019	-.4232564	-.0378661
bf4	-.1537429	.030406	-5.06	0.000	-.2133376	-.0941483
bf7	-.1191117	.0581157	-2.05	0.040	-.2330165	-.0052069
deaw2	.335947	.1907639	1.76	0.078	-.0379434	.7098375
_cons	-3.075185	.953438	-3.23	0.001	-4.94389	-1.206481

```

457 .
458 . di as input "female trimmed model for dose-home care impact in wv 3: dose no
    > t signif"
    female trimmed model for dose-home care impact in wv 3: dose not signif

459 . di as input " female dose is not signif as main effect in dose - homecare im
    > pact "
    female dose is not signif as main effect in dose - homecare impact

460 . di as input " no female moderate interactions for dose-homecare impact"
    no female moderate interactions for dose-homecare impact

461 .
462 . scalar SigDoseHmcrFw2 = "yes"

463 . scalar MainEffhmcrFw2= "age radhlw2 b4 avgcumdosew2 inc2w2"

464 . scalar list
    MainEffhmcrFw2 = age radhlw2 b4 avgcumdosew2 inc2w2
    hmcrMedFw2 = radhlw2 age bf40 bf4m bf4 bf1
    MainEffwkFw2 = age
    MainEffwkMw2 = age
    inthobMedMw2 = age
    inthobMw2 = age
    sxlifeMedMw2 = age illw2
    SigDoseSxlifeFw2 = no
    MainEffsxlifeFw2 = age radhlw2 bf4 bf4m
    PrbfmhmModMw2 = none
    MainEffProbSocFw2 = age radhlw2 avgcumdosew2 bf4
    MainEffPrbsocMw2 = age radhlw2 shjobw2
    hmcrModMw2 = none
    MainEffhmcrMw2 = age
    wkMedFw2 = age b4
    wkMedMw2 = age bf4
    MainEffVactnMw2 = age radhlw2
    MainEffsxlifeMw2 = age bf4 bf40 shjobw2 shrelaw2 radhlw2
    MainEffPrbfmhmMw2 = bf4 bf6 bf7
    ProbsocMedFw2 = age bf4 radhlw2
    hmcareMedFw2 = age bf4
    WkhmcrMw2 = age b4
    MainEffhmcrw2 = age
    hmcrModFw2 = none
    SigDoseHmcrFw2 = yes
    NumhmcrModMw2 = none
    SigDosehmcrMw2 = no
    SigdosehmcrFw2 = yes
    hmcrMedMw2 = age ageXillw2
    SigDosehmcrFw2 = no
    MainEffhmcareMw2 = age

```

```

WkMedMw2 = age ageXillw2
wkMedFw3 = radhlw3 age ageXillw3 bf40 bf4m bf1
VactnMedFw2 = age illw2 radhlw2
VactnMedMw2 = age illw2
VacatnModFw2 = none
MainEffVactnFw2 = age radhlw2 bf7m
SigDoseVactnFw2 = no
VactnModMw2 = none
vactnModMw2 = none
SigDoseVactnMw2 = no
inthobMedFw2 = age bf4 illw2 bf4m
InthbModFw2 = none
MainEffInthbFw2 = age radhlw2 bf4
SigdoseInthbFw2 = no
InthbModMw2 = none
MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
MainEffMw2 = radhlw2 bf4 bf40
SigdoseMEinthob = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
SxLifeModFw2 = no
sxlifeModFw2 = none
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf4 bf6 bf7
ProbsocMedMw2 = age
ProbsocModFw2 = none
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
PrbsocModMw2 = none
SigdoseMw2 = none
hmcareMedMw2 = age
hmcareModFw2 = none
MainEffhmcarew2 = age
SigdoseHmcareFw2 = no
hmcareModMw2 = none
SigDoseHmcareMw2 = no
NameMedMw2 = age ageXillw2
NumModMw2 = none
SigDosehmcareMw2 = no

```

```

SigDoseWKMw2 = no
  WkMedFw2 = age bf4
  WkModFw2 = none
  WKModMw2 = none
SigDoseWkMw2 = no
SigDoseWkFw2 = no
SigDoseFw2 = no
  wkModFw2 = none
  wkModMw2 = none
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
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no

```

```

465 .
466 . title4 "Fully trimmed Female Main effects model for dose=> homecare Wave 2"

```

Fully trimmed Female Main effects model for dose=> homecare Wave 2

```

467 .   logit hp2hmcare age radhlw2 occ1w2-occ8w2 inclw2-inc4w2 ///
>       avgcumdosew2 bf4 bf7 if gender==2

```

```

Iteration 0:   log likelihood = -233.72859
Iteration 1:   log likelihood = -173.85645
Iteration 2:   log likelihood = -171.23111
Iteration 3:   log likelihood = -171.21316
Iteration 4:   log likelihood = -171.21315

```

Logistic regression	Number of obs	=	363
	LR chi2(17)	=	125.03
	Prob > chi2	=	0.0000
Log likelihood = -171.21315	Pseudo R2	=	0.2675

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0819767	.0142028	5.77	0.000	.0541397	.1098137
radhlw2	-.0078775	.0044202	-1.78	0.075	-.016541	.0007859
occ1w2	-2.242774	1.301364	-1.72	0.085	-4.793401	.3078536
occ2w2	-1.846605	1.328554	-1.39	0.165	-4.450523	.7573135
occ3w2	-1.427003	1.326565	-1.08	0.282	-4.027023	1.173016
occ4w2	-2.012805	1.40509	-1.43	0.152	-4.76673	.7411195
occ5w2	-3.538941	1.580125	-2.24	0.025	-6.63593	-.4419532
occ6w2	-3.768093	1.762492	-2.14	0.033	-7.222513	-.3136722
occ7w2	-1.546761	1.332033	-1.16	0.246	-4.157497	1.063975
occ8w2	-1.768467	1.488276	-1.19	0.235	-4.685435	1.148501

inclw2	1.822692	1.361957	1.34	0.181	-.8466958	4.492079
inc2w2	2.706743	1.329501	2.04	0.042	.100968	5.312517
inc3w2	2.344358	1.336604	1.75	0.079	-.2753368	4.964053
inc4w2	2.501679	1.567188	1.60	0.110	-.5699539	5.573311
avgcumdosew2	-.2371789	.0989186	-2.40	0.016	-.4310558	-.0433019
bf4	-.1518277	.0301026	-5.04	0.000	-.2108276	-.0928278
bf7	-.1176948	.0584053	-2.02	0.044	-.2321671	-.0032225
_cons	-3.013568	.9447932	-3.19	0.001	-4.865329	-1.161807

```

468 .
469 . title4 "Super trimmed Female Main effects model for dose=> homecare Wave 2"

```

Super trimmed Female Main effects model for dose=> homecare Wave 2

```

470 . sw, pr(.1): logit hp2hmcare age radhlw2 occ1w2-occ8w2 inclw2-inc4w2 ///
>     avgcumdosew2 bf4 bf7 if gender==2
      begin with full model
p = 0.2821 >= 0.1000 removing occ3w2
p = 0.6236 >= 0.1000 removing occ7w2
p = 0.6398 >= 0.1000 removing occ8w2
p = 0.4881 >= 0.1000 removing inclw2
p = 0.4545 >= 0.1000 removing occ2w2
p = 0.5211 >= 0.1000 removing occ4w2
p = 0.3199 >= 0.1000 removing inc4w2
p = 0.1918 >= 0.1000 removing inc3w2
p = 0.1378 >= 0.1000 removing occ1w2
p = 0.1362 >= 0.1000 removing occ6w2

```

Logistic regression	Number of obs	=	363
	LR chi2(7)	=	113.92
	Prob > chi2	=	0.0000
Log likelihood = -176.76786	Pseudo R2	=	0.2437

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0809999	.0131645	6.15	0.000	.0551979	.1068019
radhlw2	-.008483	.0042861	-1.98	0.048	-.0168836	-.0000824
bf4	-.1415224	.0280339	-5.05	0.000	-.1964677	-.086577
avgcumdosew2	-.2113393	.0943544	-2.24	0.025	-.3962706	-.026408
bf7	-.1047511	.0556644	-1.88	0.060	-.2138513	.0043492
inc2w2	.5976184	.274636	2.18	0.030	.0593418	1.135895
occ5w2	-1.577132	.9099374	-1.73	0.083	-3.360576	.2063126
_cons	-2.87938	.823917	-3.49	0.000	-4.494227	-1.264532

```

471 .
472 . cap gen radhlw2Xd2 = radhlw2*avgcumdosew2

473 . cap gen inc2w2Xd2 = inc2w2*avgcumdosew2

474 .
475 . title2 "female main effect plus interaction model"

```

```

title2: female main effect plus interaction model
                                Date and time: 17 Jun 2012    10:06:04
                                Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2
                                Stata data file: chwide16june2012.dta
> has 2384 variables and 703 observations

```

```

female main effect plus interaction model

```

```

476 . xi:logit hp2hmcare age avgcumdosew2 bf4 ageXd2 bf4Xd2 radhlw2Xd2 ///
> inc2w2 inc2w2Xd2 if gender==2

```

```

Iteration 0: log likelihood = -233.72859
Iteration 1: log likelihood = -182.44019
Iteration 2: log likelihood = -181.11746
Iteration 3: log likelihood = -181.11148
Iteration 4: log likelihood = -181.11148

```

Logistic regression	Number of obs	=	363
	LR chi2(8)	=	105.23
	Prob > chi2	=	0.0000
Log likelihood = -181.11148	Pseudo R2	=	0.2251

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0738073	.0154412	4.78	0.000	.0435431	.1040715
avgcumdosew2	-.805145	.920628	-0.87	0.382	-2.609543	.9992527
bf4	-.1260231	.0343389	-3.67	0.000	-.1933261	-.0587202
ageXd2	.0062691	.013444	0.47	0.641	-.0200806	.0326189
bf4Xd2	.0040762	.0279505	0.15	0.884	-.0507058	.0588581
radhlw2Xd2	-.0002867	.0024983	-0.11	0.909	-.0051834	.0046099
inc2w2	.3655336	.357839	1.02	0.307	-.335818	1.066885
inc2w2Xd2	.2525036	.3220194	0.78	0.433	-.3786429	.8836502
_cons	-3.100171	.9665279	-3.21	0.001	-4.994531	-1.205811

```

477 .
478 . * there are no significant moderators for female dose=hmcare relationship
479 . scalar hmcrModFw2 = "none"

480 .
481 .
482 .
483 . scalar SigdosehmcrFw2="yes"

484 .
485 .
486 . scalar MainEffhmcrw2 = "age"

487 . scalar hmcrModFw2 = "none"

488 .
489 .
490 . title4 "Mediator relationships for home care are tested below"

```

Mediator relationships for home care are tested below

```

491 . title4 "H1 pt 2 wave 2 Mediation of home care testing for males"

```

H1 pt 2 wave 2 Mediation of home care testing for males

```

492 .
493 . * male hp2wk w2 mediators: testing b4 and b40
494 .
495 .
496 . correlate bf4 age if gender==1
    (obs=340)

```

	bf4	age
bf4	1.0000	
age	-0.4041	1.0000

```

497 .
498 . des bf4

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```

499 . title4 "Possible male mediators in wave 2" "bf4 can be a male mediator in wa
> ve 2"

```

Possible male mediators in wave 2

```

500 . glm bf4 age avgcumdosew2 if gender==1, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-996.64953**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	20.7725
Deviance = 7000.331927	(1/df) Deviance	=	20.7725
Pearson = 7000.331927	(1/df) Pearson	=	20.7725

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

Log likelihood = -996.6495299	<u>AIC</u>	=	5.880291
	<u>BIC</u>	=	5035.977

bf4	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
age	-.1659274	.0203994		-8.13	0.000	-.2059095	-.1259453
avgcumdosew2	.0636104	.0995687		0.64	0.523	-.1315406	.2587614
_cons	20.59657	1.026594		20.06	0.000	18.58448	22.60866

```
501 . glm hp2hmcare bf4 age if gender==1, fam(binomial) link(probit) irls scale(de
> v)
```

```
Iteration 1:  deviance =    265.85
Iteration 2:  deviance =   261.7102
Iteration 3:  deviance =   261.5892
Iteration 4:  deviance =   261.5887
Iteration 5:  deviance =   261.5887
Iteration 6:  deviance =   261.5887
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  ML Fisher scoring                 Residual df    =       337
                   (IRLS EIM)                          Scale parameter =        1
Deviance          =   261.5886708                       (1/df) Deviance =   .7762275
Pearson           =   284.8259081                       (1/df) Pearson  =   .8451807
```

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

```
BIC                                     =  -1702.766
```

hp2hmcare	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.1318123	.0159309	-8.27	0.000	-.1630363	-.1005883
age	.0141501	.0068474	2.07	0.039	.0007294	.0275707
_cons	-.0621746	.4509187	-0.14	0.890	-.945959	.8216099

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

```
502 . title4 "age and bf4 can be wave 2 home care mediators for men"
```

```
age and bf4 can be wave 2 home care mediators for men
```

```
503 .
```

```

504 .
505 . title4 "Age can be a male mediator in wave 2"

```

Age can be a male mediator in wave 2

```

506 . glm age avgcumdosew2 if gender==1, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853

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

Log likelihood = -1330.6004	<u>AIC</u>	=	7.838826
	<u>BIC</u>	=	47947.46

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```

507 . glm hp2hmcare age if gender==1, fam(binomial) link(probit) irls scale(dev)

```

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.)

508 . title4 "age could be a home care mediator for men in wave 2"

age could be a home care mediator for men in wave 2

509 .

510 .

511 . scalar WkhmcrMw2 = "age b4"

512 . * moderate negative correlation between bf4 and age generates ///

> * annihilation of effect among men in wave 2"

513 .

514 .

515 . title4 "Testing possible female home care mediators for home care in wave 2"

Testing possible female home care mediators for home care in wave 2

516 .

517 . title4 "Test of age as possible female mediator in wave 2"

Test of age as possible female mediator in wave 2

518 . glm age avgcumdosew2 if gender==2, fam(gauss) link(identity)

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

Generalized linear models

Optimization : **ML**

Deviance = **49427.52828**

Pearson = **49427.52828**

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

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

No. of obs = **363**

Residual df = **361**

Scale parameter = **136.9184**

(1/df) Deviance = **136.9184**

(1/df) Pearson = **136.9184**

[**Gaussian**]

[**Identity**]

Log likelihood = **-1406.940271**

AIC = **7.762756**

BIC = **47299.65**

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

```
519 . glm hp2hmcare age if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
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)      [Bernoulli]
Link function      : g(u) = invnorm(u)  [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.)
```

```
520 . title4 "age is a possible mediator for women"
```

```
age is a possible mediator for women
```

```

521 .
522 .
523 . title4 "Test of b40 as female mediator of home care in wave 2"

```

Test of b40 as female mediator of home care in wave 2

```

524 . glm bf40 age avgcumdosew2 if gender==2, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-812.90018**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	360
	Scale parameter	=	5.202871
Deviance = 1873.033605	(1/df) Deviance	=	5.202871
Pearson = 1873.033605	(1/df) Pearson	=	5.202871

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

	<u>AIC</u>	=	4.495318
Log likelihood = -812.900181	<u>BIC</u>	=	-248.9514

bf40	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
age	.0344949	.0102598	3.36	0.001	.0143862	.0546037
avgcumdosew2	.1276677	.0881819	1.45	0.148	-.0451657	.3005011
_cons	1.318795	.5213154	2.53	0.011	.2970355	2.340554

```

525 . glm hp2hmcare bf40 age if gender==2, fam(binomial) link(probit) irls scale(
> dev)

```

Iteration 1: deviance = **393.1464**
Iteration 2: deviance = **393.0302**
Iteration 3: deviance = **393.0302**
Iteration 4: deviance = **393.0302**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 393.0302033	(1/df) Deviance	=	1.091751
Pearson = 376.1478629	(1/df) Pearson	=	1.044855

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

BIC = -1728.955

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.0261466	.0330724	0.79	0.429	-.0386742	.0909673
age	.0524779	.0070473	7.45	0.000	.0386654	.0662903
_cons	-3.184271	.375224	-8.49	0.000	-3.919696	-2.448845

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

526 . title4 "b40 with age is a mediator for women"

b40 with age is a mediator for women

527 .

528 .

529 . title4 "bf40 Test of female mediation of home care in wave 2"

bf40 Test of female mediation of home care in wave 2

530 . glm bf40 avgcumdosew2 if gender==2, fam(gauss) link(identity)

Iteration 0: log likelihood = -818.51169

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

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

Link function : g(u) = u [Identity]

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

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

```
531 . glm hp2hmcare bf40 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1:  deviance =  462.764
Iteration 2:  deviance =  462.2054
Iteration 3:  deviance =  462.2053
Iteration 4:  deviance =  462.2053
```

```
Generalized linear models               No. of obs      =       363
Optimization      :  MQL Fisher scoring  Residual df      =       361
                    (IRLS EIM)          Scale parameter =         1
Deviance          =  462.2053395        (1/df) Deviance =  1.280347
Pearson           =  362.3613268        (1/df) Pearson =  1.003771
```

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

```
BIC                                     = -1665.674
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.0666058	.0327979	2.03	0.042	.0023231	.1308886
_cons	-.6159451	.1313241	-4.69	0.000	-.8733356	-.3585546

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

```
532 . title4 "bf40 alone is a mediator for women"
```

```
bf40 alone is a mediator for women
```

```
533 .
```

```
534 .
```

```
535 . title4 "bf4 Test of female mediation of home care in wave 2"
```

```
bf4 Test of female mediation of home care in wave 2
```

```
536 . glm bf4 avgcumdosew2 if gender==2, fam(gauss) link(identity)
```

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

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

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

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

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

```
537 . glm hp2hmcare bf4 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1: deviance = 410.1424
Iteration 2: deviance = 410.1166
Iteration 3: deviance = 410.1166
Iteration 4: deviance = 410.1166
```

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	361
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 410.1166157	(1/df) Deviance	=	1.136057
Pearson	= 357.1140873	(1/df) Pearson	=	.9892357

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

	BIC	=	-1717.763
--	-----	---	-----------

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1024685	.0149808	-6.84	0.000	-.1318304	-.0731067
_cons	.6214741	.1665648	3.73	0.000	.295013	.9479351

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

538 . title4 "bf4 alone is a mediator for women"

bf4 alone is a mediator for women

539 .

540 .

541 .

542 . title4 "Test of female mediation of home care in wave 2"

Test of female mediation of home care in wave 2

543 . glm illw2 avgcumdosew2 if gender==2, fam(gauss) link(identity)

Iteration 0: log likelihood = -463.51524

Generalized linear models

Optimization : ML

Deviance = 273.2340487

Pearson = 273.2340487

No. of obs = 363

Residual df = 361

Scale parameter = .756881

(1/df) Deviance = .756881

(1/df) Pearson = .756881

Variance function: $V(u) = 1$

[Gaussian]

Link function : $g(u) = u$

[Identity]

Log likelihood = -463.5152411

AIC = 2.564822

BIC = -1854.645

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

```
544 . glm hp2hmcare illw2 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1:  deviance = 466.1156
Iteration 2:  deviance = 465.4957
Iteration 3:  deviance = 465.4956
Iteration 4:  deviance = 465.4956
```

```
Generalized linear models               No. of obs      =       363
Optimization      :  MQL Fisher scoring  Residual df      =       361
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 465.4955997         (1/df) Deviance = 1.289461
Pearson           = 362.823507          (1/df) Pearson  = 1.005051
```

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

```
BIC                                     = -1662.384
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.1070451	.0863777	1.24	0.215	-.0622522	.2763423
_cons	-.4461214	.0854256	-5.22	0.000	-.6135525	-.2786904

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

```
545 . title4 "illw2 alone is not a mediator for women"
```

```
illw2 alone is not a mediator for women
```

```
546 .
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547 .
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548 .
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549 .
```

```
550 . title4 "Test of female mediation of home care in wave 2"
```

```
Test of female mediation of home care in wave 2
```

```
551 . mvreg bf4 age bf40 = avgcumdosew2 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.151001	0.0249	9.209323	0.0026
age	363	2	11.70121	0.0306	11.37694	0.0008
bf40	363	2	2.313305	0.0114	4.155047	0.0422

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew2	-.595012	.1960703	-3.03	0.003	-.9805954	-.2094285
_cons	11.02048	.3223763	34.19	0.000	10.38651	11.65445
age						
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6264181	2.378231
_cons	48.86944	.7323225	66.73	0.000	47.42929	50.3096
bf40						
avgcumdosew2	.1794903	.0880548	2.04	0.042	.0063255	.3526551
_cons	3.004543	.1447786	20.75	0.000	2.719828	3.289259

```
552 . glm hp2hmcare bf4 age bf40 if gender==2, fam(binomial) link(probit) irls ///
> scale(dev)
```

```
Iteration 1: deviance = 373.2413
Iteration 2: deviance = 372.8437
Iteration 3: deviance = 372.8436
Iteration 4: deviance = 372.8436
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 372.8435707	(1/df) Deviance	=	1.038561
Pearson = 384.2294832	(1/df) Pearson	=	1.070277

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

BIC = -1743.247

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.0701088	.0159082	-4.41	0.000	-.1012882	-.0389293
age	.0419129	.007264	5.77	0.000	.0276756	.0561501
bf40	-.0040389	.0340124	-0.12	0.905	-.070702	.0626242
_cons	-1.841186	.4704258	-3.91	0.000	-2.763204	-.9191686

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

```
553 . title4 "When bf4 bf40 & age are together" ///
> "only age & b4 are a wave 2 mediators for women"
```

When bf4 bf40 & age are together

```
554 .
555 .
556 .
557 .
558 . title "Test of female mediation of home care in wave 2"
```

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```

```
559 . mvreg bf4 age bf40 illw2 = avgcumdosew2 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.151001	0.0249	9.209323	0.0026
age	363	2	11.70121	0.0306	11.37694	0.0008
bf40	363	2	2.313305	0.0114	4.155047	0.0422
illw2	363	2	.8699891	0.0380	14.24594	0.0002

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew2	-.595012	.1960703	-3.03	0.003	-.9805954	-.2094285
_cons	11.02048	.3223763	34.19	0.000	10.38651	11.65445
age						
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6264181	2.378231
_cons	48.86944	.7323225	66.73	0.000	47.42929	50.3096
bf40						
avgcumdosew2	.1794903	.0880548	2.04	0.042	.0063255	.3526551
_cons	3.004543	.1447786	20.75	0.000	2.719828	3.289259
illw2						
avgcumdosew2	.1249912	.0331157	3.77	0.000	.0598673	.1901152
_cons	.301285	.0544484	5.53	0.000	.1942091	.4083609

```
560 . glm hp2hmcare bf4 age bf40 illw2 if gender==2, fam(binomial) ///
> link(probit) irls scale(dev)
```

```
Iteration 1: deviance = 371.4357
Iteration 2: deviance = 371.0168
Iteration 3: deviance = 371.0167
Iteration 4: deviance = 371.0167
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	358
(IRLS EIM)	Scale parameter	=	1
Deviance = 371.0167043	(1/df) Deviance	=	1.03636
Pearson = 385.0960041	(1/df) Pearson	=	1.075687

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

```
BIC = -1739.18
```

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.0756726	.0166172	-4.55	0.000	-.1082417	-.0431034
age	.04214	.0072721	5.79	0.000	.0278868	.0563931
bf40	.0027501	.0343366	0.08	0.936	-.0645483	.0700486
illw2	-.1146115	.0858363	-1.34	0.182	-.2828475	.0536245
_cons	-1.768282	.4754356	-3.72	0.000	-2.700118	-.8364451

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

```

561 . qui: {
      When all are together only age and b4 are a wave 2 mediators for women

562 .
563 .
564 . scalar hmcrMedFw2 = "age bf4"

565 .
566 . scalar SigDosehmcrMw2 = "no"

567 . scalar MainEffhmcrMw2 = "age"

568 . scalar MainEffhmcrFw2 = "age"

569 . scalar hmcrFw2 = "none"

570 .
571 .
572 .
573 .
574 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-1693.4076**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.972986
Log likelihood = -1693.407647	<u>BIC</u>	=	419831.3

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

```
575 . glm hp2hmcare radhlw2 if gender==1 , fam(binomial) irls scale(dev) link(prob
> it)
```

```
Iteration 1:  deviance = 320.2142
Iteration 2:  deviance = 319.4143
Iteration 3:  deviance = 319.4134
Iteration 4:  deviance = 319.4134
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 319.4134212	(1/df) Deviance	=	.9450101
Pearson = 343.7631942	(1/df) Pearson	=	1.017051

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

```
BIC = -1650.77
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0113273	.0022041	5.14	0.000	.0070074	.0156472
_cons	-1.415444	.1449647	-9.76	0.000	-1.69957	-1.131318

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

```
576 .
```

```

577 .
578 .
579 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-1791.2233**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1137.567
Deviance = 410661.5604	(1/df) Deviance	=	1137.567
Pearson = 410661.5604	(1/df) Pearson	=	1137.567
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.880018
Log likelihood = -1791.223306	<u>BIC</u>	=	408533.7

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

```

580 . glm hp2hmcare radhlw2 if gender==2 , fam(binomial) irls scale(dev) link(prob
> it)

```

Iteration 1: deviance = **465.9397**
 Iteration 2: deviance = **465.344**
 Iteration 3: deviance = **465.3439**
 Iteration 4: deviance = **465.3439**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 465.3438602	(1/df) Deviance	=	1.289041
Pearson = 362.9626143	(1/df) Pearson	=	1.005437
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	BIC	=	-1662.536

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
radhlw2	.0029148	.0022776	1.28	0.201	-.0015493	.0073789
_cons	-.5772317	.1586961	-3.64	0.000	-.8882703	-.266193

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

```

581 .
582 . scalar hmcareMedMw2 = "age "

583 . scalar hmcareMedFw2 = "age bf4"

584 . set more off

585 . scalar list
      hmcrFw2 = none
MainEffhmcrFw2 = age
hmcrMedFw2 = age bf4
MainEffwkFw2 = age
MainEffwkMw2 = age
inthobMedMw2 = age
  inthobMw2 = age
sxlifeMedMw2 = age illw2
SigDoseSxlifeFw2 = no
MainEffsxlifeFw2 = age radhlw2 bf4 bf4m
PrbfmhmModMw2 = none
MainEffProbSocFw2 = age radhlw2 avgcumdosew2 bf4
MainEffPrbsocMw2 = age radhlw2 shjobw2
hmcrModMw2 = none
MainEffhmcrMw2 = age
  wkMedFw2 = age b4
  wkMedMw2 = age bf4
MainEffVactnMw2 = age radhlw2
MainEffsxlifeMw2 = age bf4 bf40 shjobw2 shrelaw2 radhlw2
MainEffPrbfmhmMw2 = bf4 bf6 bf7
ProbsocMedFw2 = age bf4 radhlw2
hmcareMedFw2 = age bf4
  WkhmcrMw2 = age b4
MainEffhmcrw2 = age
hmcrModFw2 = none
SigDoseHmcrFw2 = yes
NumhmcrModMw2 = none
SigDosehmcrMw2 = no
SigDosehmcrFw2 = yes
hmcrMedMw2 = age ageXillw2
SigDosehmcrFw2 = no
MainEffhmcareMw2 = age

```

```

WkMedMw2 = age ageXillw2
wkMedFw3 = radhlw3 age ageXillw3 bf40 bf4m bf1
VactnMedFw2 = age illw2 radhlw2
VactnMedMw2 = age illw2
VacatnModFw2 = none
MainEffVactnFw2 = age radhlw2 bf7m
SigDoseVactnFw2 = no
VactnModMw2 = none
vactnModMw2 = none
SigDoseVactnMw2 = no
inthobMedFw2 = age bf4 illw2 bf4m
InthbModFw2 = none
MainEffInthbFw2 = age radhlw2 bf4
SigdoseInthbFw2 = no
InthbModMw2 = none
MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
MainEffMw2 = radhlw2 bf4 bf40
SigdoseMEinthob = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
SxLifeModFw2 = no
sxlifeModFw2 = none
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf4 bf6 bf7
ProbsocMedMw2 = age
ProbsocModFw2 = none
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
PrbsocModMw2 = none
SigdoseMw2 = none
hmcareMedMw2 = age
hmcareModFw2 = none
MainEffhmcarew2 = age
SigdoseHmcareFw2 = no
hmcareModMw2 = none
SigDoseHmcareMw2 = no
NameMedMw2 = age ageXillw2
NumModMw2 = none
SigDosehmcareMw2 = no

```

```

SigDoseWKMw2 = no
  WkMedFw2 = age bf4
  WkModFw2 = none
  WKModMw2 = none
SigDoseWkMw2 = no
SigDoseWkFw2 = no
SigDoseFw2 = no
  wkModFw2 = none
  wkModMw2 = none
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
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no

```

```

586 .
587 . * conclusion "age & illw2 are main effects as possible male & female mediato
> rs"
588 . * conclusion title "their interaction is not a mediator"
589 .
590 . title4 "2. summary matrix construction for H1 pt 2 wave 2 dose=>Home care im
> pact"

```

```

2. summary matrix construction for H1 pt 2 wave 2 dose=>Home care impact

```

```

591 . set more off

592 . matrix define hmcMw2 = J(1,8, 0)

593 . matrix define hmcFw2 = J(1,8, 0)

594 . matrix colnames hmcMw2= hypnum ptnum wave gender medsig numMA sig numModsi
> g ///
> numMed

```

```

595 . matrix colnames hmcFw2= hypnum ptnum wave gender medsig numMASig numModsi
    > g ///
    > numMed

596 . matrix rownames hmcMw2 = hmcareM

597 . matrix rownames hmcFw2 = hmcareF

598 . matrix define hmcMw2= (1, 2, 3, 1, 0 , 1, 0 , 1 )

599 . matrix define hmcFw2= (1, 2, 3, 2, 1 ,1, 0 , 2 )

600 . matrix define H1pt2w2 = ( wkMw2 \ wkFw2 \ hmcMw2 \ hmcFw2)

601 . matrix colnames H1pt2w2 = hypnum ptnum wave gender medsig numMASig numM
    > odsig numMed

602 . matrix colnames H1pt2w2 = hypnum ptnum wave gender medsig numMASig numM
    > odsig numMed

603 . matrix rownames H1pt2w2 = wkMw2 wkFw2 hmcMw2 hmcFw2

604 . matlist H1pt2w2

```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2	0	2					
	wkFw2	1	2	2	2	0	
> 1	0	2					
	hmcMw2	1	2	3	1	0	
> 1	0	1					
	hmcFw2	1	2	3	2	1	
> 1	0	2					

```

605 .
606 . * see scalar list for names of variables
607 . scalar list
MainEffhmcrFw2 = age
hmcrMedFw2 = age bf4
MainEffwkFw2 = age
MainEffwkMw2 = age
inthobMedMw2 = age
    inthobMw2 = age
sxlifeMedMw2 = age illw2
SigDoseSxlifeFw2 = no
MainEffsxlifeFw2 = age radhlw2 bf4 bf4m
PrbfmhmModMw2 = none
MainEffProbSocFw2 = age radhlw2 avgcumdosew2 bf4
MainEffPrbsocMw2 = age radhlw2 shjobw2
hmcrModMw2 = none
MainEffhmcrMw2 = age
    wkMedFw2 = age b4
    wkMedMw2 = age bf4
MainEffVactnMw2 = age radhlw2
MainEffsxlifeMw2 = age bf4 bf40 shjobw2 shrelaw2 radhlw2
MainEffPrbfmhmMw2 = bf4 bf6 bf7
ProbsocMedFw2 = age bf4 radhlw2
hmcareMedFw2 = age bf4
    WkhmcrMw2 = age b4
MainEffhmcrw2 = age
hmcrModFw2 = none
SigDoseHmcrFw2 = yes
NumhmcrModMw2 = none
SigDosehmcrMw2 = no
SigDosehmcrFw2 = yes
hmcrMedMw2 = age ageXillw2
SigDosehmcrFw2 = no
MainEffhmcareMw2 = age
    WkMedMw2 = age ageXillw2
    wkMedFw3 = radhlw3 age ageXillw3 bf40 bf4m bf1
VactnMedFw2 = age illw2 radhlw2
VactnMedMw2 = age illw2
VacatnModFw2 = none
MainEffVactnFw2 = age radhlw2 bf7m
SigDoseVactnFw2 = no
VactnModMw2 = none
vactnModMw2 = none
SigDoseVactnMw2 = no
inthobMedFw2 = age bf4 illw2 bf4m
InthbModFw2 = none
MainEffInthbFw2 = age radhlw2 bf4
SigdoseInthbFw2 = no
InthbModMw2 = none

```

```

MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
MainEffMw2 = radhlw2 bf4 bf40
SigdoseMEinthob = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
SxLifeModFw2 = no
sxlifeModFw2 = none
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf4 bf6 bf7
ProbsocMedMw2 = age
ProbsocModFw2 = none
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
PrbsocModMw2 = none
SigdoseMw2 = none
hmcareMedMw2 = age
hmcareModFw2 = none
MainEffhmcarew2 = age
SigdoseHmcareFw2 = no
hmcareModMw2 = none
SigDoseHmcareMw2 = no
NameMedMw2 = age ageXillw2
  NumModMw2 = none
SigDosehmcareMw2 = no
SigDoseWKMw2 = no
  WkMedFw2 = age bf4
  WkModFw2 = none
  WKModMw2 = none
SigDoseWkMw2 = no
SigDoseWkFw2 = no
SigDoseFw2 = no
  wkModFw2 = none
  wkModMw2 = none
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
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no

```

```
608 .  
609 . * X * missing the number of main effects in the trimmed models  
610 .  
611 . ///////////////////////////////////////  
    > *----- Chunk 4   Dose social problem impact relationship HP2probsoc  
612 .  
613 .  
614 . title "3.  H1 part 2 wave 2   Dose - HP2probsoc impact tested"  
  
*****  
> *  
*****  
> *  
*****                                     ****  
> *  
*****                                     ****  
> *  
*****      3.  H1 part 2 wave 2   Dose - HP2probsoc impact tested          ****  
> *  
*****                                     ****  
> *  
*****                                     ****  
> *  
*****                                     ****  
> *  
*****                                17 Jun 2012     10:06:37     ****  
> *  
*****  
> *  
*****  
> *
```

```
615 .  
616 . forvalues j = 2/2 {  
    2. set more off  
    3.
```

```

617 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
    >   bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
    4.
618 .   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.
619 .
620 .       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   difficult iterate(50)
    11.               estat class
    12.               estat gof
    13.               fitstat
    14. }
    15. }
    16. }

```

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

inc2w2	double %15.0g	LABJ	basic neccessities in 1996 Income is just sufficient for basic neccessities in 1996
inc3w2	double %15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double %15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float %9.0g		bf1 = max(0, kzchorn - 40)
bf4	float %9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float %9.0g		bf9= max(0, 30 - shhlw1)
bf11	float %9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float %9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float %9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float %9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float %9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2probsoc for wave= 2

chunk 4 H1 test:Gender= 1 model Wave = 2 for hp2hmcare

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

note: _Ieduc_4 != 0 predicts failure perfectly
 _Ieduc_4 dropped and 12 obs not used

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

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

note: occ6w2 != 0 predicts failure perfectly
 occ6w2 dropped and 4 obs not used

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

note: occ8w2 != 0 predicts failure perfectly
 occ8w2 dropped and 43 obs not used

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

note: marrw25 != 0 predicts failure perfectly
 marrw25 dropped and 4 obs not used

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

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 3 obs not used

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

note: _Ieduc_6 omitted because of collinearity

note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	228
	LR chi2(34)	=	103.91
	Prob > chi2	=	0.0000
Log likelihood = -52.36582	Pseudo R2	=	0.4980

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0906854	.0339814	2.67	0.008	.0240831	.1572876
_Ieduc_2	-.0346926	1.161856	-0.03	0.976	-2.311888	2.242503
_Ieduc_3	-.6886648	.7207042	-0.96	0.339	-2.101219	.7238895
_Ieduc_4	0	(omitted)				
_Ieduc_5	.9759744	1.063631	0.92	0.359	-1.108703	3.060652
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-.9172264	10.67202	-0.09	0.932	-21.83401	19.99955
occ2w2	-.7254984	10.66823	-0.07	0.946	-21.63485	20.18385
occ3w2	-.6714679	10.68886	-0.06	0.950	-21.62126	20.27832
occ4w2	-2.239171	10.70842	-0.21	0.834	-23.22728	18.74894
occ5w2	-.9195542	10.71455	-0.09	0.932	-21.91968	20.08057
occ6w2	0	(omitted)				
occ7w2	0	(omitted)				
occ8w2	0	(omitted)				
marrw21	11.0684	1379.375	0.01	0.994	-2692.457	2714.594
marrw22	0	(omitted)				
marrw23	8.945925	1379.375	0.01	0.995	-2694.579	2712.471
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inc1w2	.3641243	10.76623	0.03	0.973	-20.7373	21.46555
inc2w2	1.742499	10.67327	0.16	0.870	-19.17672	22.66172
inc3w2	3.371881	10.68463	0.32	0.752	-17.56961	24.31337
inc4w2	0	(omitted)				
radhlw2	.0085407	.0114129	0.75	0.454	-.0138281	.0309095
havmil	-.0006807	.0078287	-0.09	0.931	-.0160246	.0146632
avgcumdosew2	.099739	.0947343	1.05	0.292	-.0859367	.2854148
bf1	.0048596	.0179991	0.27	0.787	-.0304181	.0401372

bf4	-.3368708	.0845017	-3.99	0.000	-.5024911	-.1712504
bf6	.0294921	.0150976	1.95	0.051	-.0000987	.0590829
bf7	.2107792	.1280115	1.65	0.100	-.0401186	.4616771
bf14	-.0000508	.0001111	-0.46	0.648	-.0002685	.0001669
bf15	0	(omitted)				
bf40	.3587504	.202109	1.78	0.076	-.0373759	.7548768
deaw2	-.2425986	.5320938	-0.46	0.648	-1.285483	.8002861
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0583869	.772113	-0.08	0.940	-1.571701	1.454927
movew2	.534895	.8346364	0.64	0.522	-1.100962	2.170752
illw2	.3093012	.430894	0.72	0.473	-.5352355	1.153838
shfamw2	-.0138199	.0107438	-1.29	0.198	-.0348774	.0072375
shhlw2	-.0108054	.0127581	-0.85	0.397	-.0358108	.0141999
shjobw2	.024033	.0121387	1.98	0.048	.0002416	.0478244
shrelaw2	-.0263531	.0111814	-2.36	0.018	-.0482683	-.0044379
suprtw2	.0130386	.0099595	1.31	0.190	-.0064816	.0325589
suchrw2	.0121677	.0099924	1.22	0.223	-.007417	.0317524
havmilsq	4.68e-06	9.92e-06	0.47	0.637	-.0000148	.0000241
_cons	-18.63366	1379.378	-0.01	0.989	-2722.164	2684.897

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	27	4	31
-	12	185	197
Total	39	189	228

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	69.23%
Specificity	$\Pr(- \sim D)$	97.88%
Positive predictive value	$\Pr(D +)$	87.10%
Negative predictive value	$\Pr(\sim D -)$	93.91%
False + rate for true ~D	$\Pr(+ \sim D)$	2.12%
False - rate for true D	$\Pr(- D)$	30.77%
False + rate for classified +	$\Pr(\sim D +)$	12.90%
False - rate for classified -	$\Pr(D -)$	6.09%
Correctly classified		92.98%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      228
number of covariate patterns =    228
    Pearson chi2(193) =    730.19
        Prob > chi2 =      0.0000

```

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

```

Log-Lik Intercept Only:    -104.322    Log-Lik Full Model:      -52.366
D(179):                    104.732    LR(34):                  103.912
                               Prob > LR:      0.000
McFadden's R2:             0.498    McFadden's Adj R2:      0.028
Maximum Likelihood R2:     0.366    Cragg & Uhler's R2:     0.611
McKelvey and Zavoina's R2: 0.779    Efron's R2:             0.554
Variance of y*:           14.912    Variance of error:      3.290
Count R2:                  0.930    Adj Count R2:           0.590
AIC:                       0.889    AIC*n:                  202.732
BIC:                       -867.121   BIC':                   80.686

```

Full main model for HP2probsoc for wave= 2

chunk 4 H1 test:Gender= 2 model Wave = 2 for HP2probsoc

```

i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: occ6w2 != 0 predicts failure perfectly
      occ6w2 dropped and 9 obs not used

```

```

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity

```

```

Logistic regression                                Number of obs   =      353
                                                    LR chi2(44)    =     173.44
                                                    Prob > chi2     =      0.0000
Log likelihood = -93.198778                        Pseudo R2      =      0.4820

```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1045505	.025349	4.12	0.000	.0548673	.1542337
_Ieduc_2	-12.29812	1030.765	-0.01	0.990	-2032.56	2007.964
_Ieduc_3	-12.54704	1030.765	-0.01	0.990	-2032.809	2007.715
_Ieduc_4	-11.69817	1030.765	-0.01	0.991	-2031.96	2008.564
_Ieduc_5	-11.74738	1030.765	-0.01	0.991	-2032.009	2008.515
_Ieduc_6	-12.89754	1030.765	-0.01	0.990	-2033.159	2007.364
_Ieduc_7	-14.11644	1030.817	-0.01	0.989	-2034.481	2006.248
_Ieduc_8	0 (omitted)					
occ1w2	-1.104757	3.60974	-0.31	0.760	-8.179718	5.970203

occ2w2	-1.202019	3.652886	-0.33	0.742	-8.361544	5.957506
occ3w2	.0703933	3.628444	0.02	0.985	-7.041227	7.182014
occ4w2	-1.52192	3.712086	-0.41	0.682	-8.797475	5.753635
occ5w2	-2.24588	3.84541	-0.58	0.559	-9.782745	5.290985
occ6w2	0	(omitted)				
occ7w2	-.4840598	3.61697	-0.13	0.894	-7.573191	6.605072
occ8w2	2.167215	3.89814	0.56	0.578	-5.472999	9.807428
marrw21	-.4201784	1.629029	-0.26	0.796	-3.613016	2.772659
marrw22	1.086175	1.72569	0.63	0.529	-2.296115	4.468466
marrw23	.7750978	.9250885	0.84	0.402	-1.038042	2.588238
marrw25	.532399	1.287582	0.41	0.679	-1.991215	3.056013
marrw26	0	(omitted)				
inclw2	.0603839	3.624166	0.02	0.987	-7.042851	7.163619
inc2w2	.8383333	3.595272	0.23	0.816	-6.20827	7.884937
inc3w2	.536243	3.60018	0.15	0.882	-6.519981	7.592467
inc4w2	.2312155	3.842475	0.06	0.952	-7.299898	7.762329
radhlw2	.0147911	.0081819	1.81	0.071	-.0012451	.0308272
havmil	.0022418	.0072934	0.31	0.759	-.0120531	.0165366
avgcumdosew2	.4925829	.2091227	2.36	0.018	.0827098	.9024559
bf1	-.0161664	.0113442	-1.43	0.154	-.0384006	.0060677
bf4	-.2331375	.0505589	-4.61	0.000	-.332231	-.1340439
bf6	.0021871	.0094776	0.23	0.817	-.0163887	.0207629
bf7	-.0615381	.1064342	-0.58	0.563	-.2701454	.1470692
bf14	8.31e-06	.0000929	0.09	0.929	-.0001737	.0001903
bf15	0	(omitted)				
bf40	-.005756	.0971846	-0.06	0.953	-.1962344	.1847223
deaw2	-.0331928	.2378427	-0.14	0.889	-.499356	.4329704
dvcew2	1.930249	1.72923	1.12	0.264	-1.45898	5.319477
sepaw2	-1.211648	2.172861	-0.56	0.577	-5.470378	3.047082
accdw2	-.6584952	.7729357	-0.85	0.394	-2.173421	.8564309
movew2	-.3688091	.9599148	-0.38	0.701	-2.250208	1.512589
illw2	.0217672	.2703514	0.08	0.936	-.5081118	.5516462
shfamw2	-.0185511	.0084341	-2.20	0.028	-.0350816	-.0020206
shhlw2	.0005321	.0080879	0.07	0.948	-.0153199	.0163841
shjobw2	-.0024716	.0076938	-0.32	0.748	-.0175512	.0126079
shrelaw2	-.0052827	.0086543	-0.61	0.542	-.0222447	.0116794
suprtw2	.0005602	.0066528	0.08	0.933	-.012479	.0135994
suchrw2	-.0036935	.00718	-0.51	0.607	-.017766	.0103791
havmilsq	-8.46e-06	.0000154	-0.55	0.582	-.0000386	.0000217
_cons	6.917383	1030.768	0.01	0.995	-2013.35	2027.185

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	53	11	64
-	20	269	289
Total	73	280	353

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	72.60%
Specificity	$\Pr(- \sim D)$	96.07%
Positive predictive value	$\Pr(D +)$	82.81%
Negative predictive value	$\Pr(\sim D -)$	93.08%
False + rate for true ~D	$\Pr(+ \sim D)$	3.93%
False - rate for true D	$\Pr(- D)$	27.40%
False + rate for classified +	$\Pr(\sim D +)$	17.19%
False - rate for classified -	$\Pr(D -)$	6.92%
Correctly classified		91.22%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      353
number of covariate patterns =    353
Pearson chi2(308) =      419.21
Prob > chi2 =      0.0000

```

Measures of Fit for logistic of HP2probsoc

Log-Lik Intercept Only:	-179.919	Log-Lik Full Model:	-93.199
D(304):	186.398	LR(44):	173.440
		Prob > LR:	0.000
McFadden's R2:	0.482	McFadden's Adj R2:	0.210
Maximum Likelihood R2:	0.388	Cragg & Uhler's R2:	0.607
McKelvey and Zavoina's R2:	0.892	Efron's R2:	0.528
Variance of y*:	30.526	Variance of error:	3.290
Count R2:	0.912	Adj Count R2:	0.575
AIC:	0.806	AIC*n:	284.398
BIC:	-1597.009	BIC':	84.685

```

621 .
622 . *-----Chunk 4 dose3 social problem impact-----no sig dose main effe
    > ct--
623 . title4 "Male trimmed models of dose and HP2probsoc relationship in Wave 2"

```

Male trimmed models of dose and HP2probsoc relationship in Wave 2

```

624 . * male models
625 .     forvalues j = 2/2 {
    2. set more off
    3. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
    4. title4 "trimmed HP2probsoc main effects models Wave 2 for H1 part 2 with
> dose ns"
    5. title4 "Wave 2 dose HP2probsoc relationship but avgcumdosew`j': Dose not
> signif"
    6. sw, pr(.1): logit HP2probsoc age radhlw2 accdw`j' `w`j'bf' shjobw`j' ill
> w`j' havmilsq ///
    >     avgcumdosew`j' shrelaw`j' if gender==1
    7.
    8.
    9.
   10. }

```

trimmed HP2probsoc main effects models Wave 2 for H1 part 2 with dose ns

Wave 2 dose HP2probsoc relationship but avgcumdosew2: Dose not signif

```

note: bf15 dropped because of collinearity
begin with full model
p = 0.9688 >= 0.1000 removing havmilsq
p = 0.8362 >= 0.1000 removing bf40
p = 0.7569 >= 0.1000 removing bf1
p = 0.4563 >= 0.1000 removing bf6
p = 0.6327 >= 0.1000 removing bf7
p = 0.3860 >= 0.1000 removing bf14
p = 0.4368 >= 0.1000 removing illw2
p = 0.3539 >= 0.1000 removing accdw2
p = 0.2376 >= 0.1000 removing radhlw2
p = 0.1378 >= 0.1000 removing avgcumdosew2

```

Logistic regression	Number of obs	=	332
	LR chi2(4)	=	82.60
	Prob > chi2	=	0.0000
Log likelihood = -78.833798	Pseudo R2	=	0.3438

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0571104	.0201616	2.83	0.005	.0175943	.0966265
bf4	-.2386201	.0424268	-5.62	0.000	-.321775	-.1554652
shjobw2	.0183809	.0063016	2.92	0.004	.0060301	.0307318
shrelaw2	-.0143444	.0067621	-2.12	0.034	-.0275978	-.0010909
_cons	-3.38883	1.393067	-2.43	0.015	-6.11919	-.6584689

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	18	6	24
-	21	287	308
Total	39	293	332

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	46.15%
Specificity	$\Pr(- \sim D)$	97.95%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	93.18%
False + rate for true ~D	$\Pr(+ \sim D)$	2.05%
False - rate for true D	$\Pr(- D)$	53.85%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	6.82%
Correctly classified		91.87%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      332
number of covariate patterns =    315
    Pearson chi2(310) =    309.74
        Prob > chi2 =      0.4935

```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-120.135	Log-Lik Full Model:	-78.834
D(327):	157.668	LR(4):	82.603
		Prob > LR:	0.000
McFadden's R2:	0.344	McFadden's Adj R2:	0.302
Maximum Likelihood R2:	0.220	Cragg & Uhler's R2:	0.428
McKelvey and Zavoina's R2:	0.483	Efron's R2:	0.343
Variance of y*:	6.358	Variance of error:	3.290
Count R2:	0.919	Adj Count R2:	0.308
AIC:	0.505	AIC*n:	167.668
BIC:	-1740.612	BIC':	-59.383

```

626 .
627 .
628 . scalar SigdoseMw2 = "none"

629 . scalar MainEffPrbsocMw2 = "age bf4 shjobw2 shrelaw2"

630 .
631 .
632 . forvalues j = 2/2 {
      2. title "trimmed HP2probsoc main effects models wave `j'" " for H1 part 2 w
> ith dose ns"
      3. title2 "Wave `j dose HP2work relationship but avgcumdosew`j': Dose not si
> gnif"
      4. }

*****
> *
*****
> *
*****
> *
*****
> *
*****
trimmed HP2probsoc main effects models wave 2
> *
*****
for H1 part 2 with dose ns
> *
*****
> *
*****
> *
*****
17 Jun 2012 10:06:58
> *
*****
> *
*****
> *

```



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

```
Iteration 0: log likelihood = -125.02372
Iteration 1: log likelihood = -101.24332
Iteration 2: log likelihood = -98.037905
Iteration 3: log likelihood = -95.91285
Iteration 4: log likelihood = -95.749868
Iteration 5: log likelihood = -95.696376
Iteration 6: log likelihood = -95.696088
Iteration 7: log likelihood = -95.696088
```

Logistic regression

```
Number of obs   =      339
LR chi2(8)      =      58.66
Prob > chi2     =      0.0000
Pseudo R2      =      0.2346
```

Log likelihood = **-95.696088**

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0770577	.0337156	2.29	0.022	.0109764	.1431391
avgcumdosew2	.0508309	3.097077	0.02	0.987	-6.019328	6.12099
radhlw2	.0197993	.0083366	2.37	0.018	.0034598	.0361387
shjobw2	.0098329	.0082287	1.19	0.232	-.0062951	.025961
ageXd2	-.0178912	.0446691	-0.40	0.689	-.1054409	.0696586
radhlw2Xd2	.0034014	.0089744	0.38	0.705	-.0141881	.0209909
shjobw2Xd2	.0078713	.0105502	0.75	0.456	-.0128068	.0285493
shrelaw2Xd2	-7.85e-06	.0047539	-0.00	0.999	-.0093253	.0093096
_cons	-7.732618	2.35884	-3.28	0.001	-12.35586	-3.109376

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	10	1	11
-	31	297	328
Total	41	298	339

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

Sensitivity	$\Pr(+ D)$	24.39%
Specificity	$\Pr(- \sim D)$	99.66%
Positive predictive value	$\Pr(D +)$	90.91%
Negative predictive value	$\Pr(\sim D -)$	90.55%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	0.34%
False - rate for true D	$\Pr(- D)$	75.61%
False + rate for classified +	$\Pr(\sim D +)$	9.09%
False - rate for classified -	$\Pr(D -)$	9.45%
Correctly classified		90.56%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      339
number of covariate patterns =    328
    Pearson chi2(319) =    362.73
        Prob > chi2 =      0.0461

```

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.024	Log-Lik Full Model:	-95.696
D(330):	191.392	LR(8):	58.655
		Prob > LR:	0.000
McFadden's R2:	0.235	McFadden's Adj R2:	0.163
Maximum Likelihood R2:	0.159	Cragg & Uhler's R2:	0.305
McKelvey and Zavoina's R2:	0.553	Efron's R2:	0.224
Variance of y*:	7.356	Variance of error:	3.290
Count R2:	0.906	Adj Count R2:	0.220
AIC:	0.618	AIC*n:	209.392
BIC:	-1731.188	BIC':	-12.047

```

639 .
640 .
641 . *---- attempt to further trim
642 . scalar PrbsocModMw2 = "none"

643 .
644 . forvalues j = 2/2 {
      2.  logit HP2probsoc age  radhlw2 shjobw`j' shrelaw2 ///
>      avgcumdosew`j' ///
>      shjobw2Xd2 if gender==1
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

```

```

Iteration 0:  log likelihood = -125.02372
Iteration 1:  log likelihood = -101.95087
Iteration 2:  log likelihood = -97.334386
Iteration 3:  log likelihood = -95.853426
Iteration 4:  log likelihood = -95.386285
Iteration 5:  log likelihood = -95.343931
Iteration 6:  log likelihood = -95.343899
Iteration 7:  log likelihood = -95.343899

```

Logistic regression	Number of obs	=	339
	LR chi2(6)	=	59.36
	Prob > chi2	=	0.0000
Log likelihood = -95.343899	Pseudo R2	=	0.2374

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0661146	.0169659	3.90	0.000	.032862	.0993672
radhlw2	.0238012	.0061541	3.87	0.000	.0117394	.0358631
shjobw2	.0124131	.0072366	1.72	0.086	-.0017703	.0265965
shrelaw2	-.0074078	.0056539	-1.31	0.190	-.0184892	.0036736
avgcumdosew2	-.8016641	.6668355	-1.20	0.229	-2.108638	.5053095
shjobw2Xd2	.0088782	.0069242	1.28	0.200	-.0046931	.0224494
_cons	-7.291581	1.220643	-5.97	0.000	-9.683998	-4.899164

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	9	3	12
-	32	295	327
Total	41	298	339

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	21.95%
Specificity	$\Pr(- \sim D)$	98.99%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	90.21%
False + rate for true ~D	$\Pr(+ \sim D)$	1.01%
False - rate for true D	$\Pr(- D)$	78.05%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	9.79%
Correctly classified		89.68%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      339
number of covariate patterns =    328
Pearson chi2(321) =      347.28
Prob > chi2 =      0.1501

```

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.024	Log-Lik Full Model:	-95.344
D(332):	190.688	LR(6):	59.360
		Prob > LR:	0.000
McFadden's R2:	0.237	McFadden's Adj R2:	0.181
Maximum Likelihood R2:	0.161	Cragg & Uhler's R2:	0.308
McKelvey and Zavoina's R2:	0.517	Efron's R2:	0.220
Variance of y*:	6.815	Variance of error:	3.290
Count R2:	0.897	Adj Count R2:	0.146
AIC:	0.604	AIC*n:	204.688
BIC:	-1743.544	BIC':	-24.404

```

645 . scalar SigDoseProbsocMw2 = "no"

646 . * xx no signific radhlw3 by dose effect
647 . * xx for males no signif dose social problem effect
648 . * xx for males no significant moderator in dose social problem effect
649 . scalar ProbSocModMw2 = "none"

650 . * female models
651 .
652 .
653 . scalar SigDoseProbsocFw2 = "yes"

654 . scalar MainEffProbSocFw2 = "age radhlw2 avgcumdosew2 bf4"

655 .
656 .
657 .
658 . title4 "H1 pt2 wave 2 trimmed female moderator model with basis functions"

```

```

H1 pt2 wave 2 trimmed female moderator model with basis functions

```

```

659 . forvalues j = 2/2 {
      2. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      3. title "trimmed HP2probsoc main effects models Wave 2 for H1 part 2 " "Dos
> e is signif Females"
      4. title "Wave 2 dose HP2probsoc relationship but avgcumdosew`j': Dose signi
> f"
      5. sw, pr(.1): logit HP2probsoc age radhlw2 illw`j' `w2bf' ///
> shrelaw`j' avgcumdosew`j' if gender==2
      6.          estat class
      7.          estat gof
      8.          fitstat
      9. }

*****
> *
*****
> *
*****
> *
*****
> *
***** trimmed HP2probsoc main effects models Wave 2 for H1 part 2 *****
> *
***** Dose is signif Females *****
> *
*****

```

```

> *
*****
> *
*****
17 Jun 2012    10:07:01    ****
> *
*****
> *
*****
> *
*****
Wave 2 dose HP2probsoc relationship but avgcumdosew2: Dose signif    ****
> *
*****
> *
*****
> *
*****
17 Jun 2012    10:07:01    ****
> *
*****
> *
*****

```

```

note: bf15 dropped because of collinearity
      begin with full model
p = 0.9211 >= 0.1000 removing illw2
p = 0.7587 >= 0.1000 removing bf14
p = 0.5303 >= 0.1000 removing bf40
p = 0.4770 >= 0.1000 removing bf7
p = 0.3763 >= 0.1000 removing bf1
p = 0.2334 >= 0.1000 removing bf6

```

Logistic regression	Number of obs	=	363
	LR chi2(5)	=	148.64
	Prob > chi2	=	0.0000
Log likelihood = -109.2514	Pseudo R2	=	0.4049

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0970773	.0185105	5.24	0.000	.0607973	.1333572
radhlw2	.0147041	.0057226	2.57	0.010	.003488	.0259202
avgcumdosew2	.4069203	.1523059	2.67	0.008	.1084062	.7054343
shrelaw2	-.0147018	.005883	-2.50	0.012	-.0262323	-.0031712
bf4	-.1790113	.0368313	-4.86	0.000	-.2511993	-.1068232
_cons	-6.193984	1.259936	-4.92	0.000	-8.663413	-3.724554

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	45	10	55
-	29	279	308
Total	74	289	363

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

Sensitivity	$\Pr(+ D)$	60.81%
Specificity	$\Pr(- \sim D)$	96.54%
Positive predictive value	$\Pr(D +)$	81.82%
Negative predictive value	$\Pr(\sim D -)$	90.58%
False + rate for true ~D	$\Pr(+ \sim D)$	3.46%
False - rate for true D	$\Pr(- D)$	39.19%
False + rate for classified +	$\Pr(\sim D +)$	18.18%
False - rate for classified -	$\Pr(D -)$	9.42%
Correctly classified		89.26%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	363
number of covariate patterns =	362
Pearson chi2(356) =	416.51
Prob > chi2 =	0.0148

Measures of Fit for **logit** of **HP2probsoc**

```

660 .
661 . foreach var in b4 shrelaw2 {
      2. cap    gen `var'Xd2 = `var'*avgcumdosew2
      3. }

662 .
663 . * testing the female moderator model with basis functions
664 . forvalues j = 2/2 {
      2. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      3. title "trimmed HP2socprob main effects  wv 3 for Hyp1 pt 2" "dose is sign
> if for females"
      4. title "Wave 2 dose HP2socprob relationship but avgcumdosew`j'" " Dose is
> signif for females"
      5. sw, pr(.1): logit HP2probsoc age radhlw2 illw`j' `w2bf' ////
>   shrelaw`j' avgcumdosew`j' b4Xd2 shrelaw2Xd2 ///
>     if gender==2

      6.                               estat class
      7.                               estat gof
      8.                               fitstat
      9. }

```



```

*****                               17 Jun 2012    10:07:11    ****
> *
*****
> *
*****
> *

*****
> *
*****
> *
*****                               ****
> *
*****                               ****
> *
*****                               ****
Wave 2 dose HP2socprob relationship but avgcumdosew2    ****
> *
*****                               ****
Dose is signif for females                               ****
> *
*****                               ****
> *
*****                               ****
> *
*****                               ****
*****                               17 Jun 2012    10:07:11    ****
> *
*****
> *
*****
> *

```

```

note: bf15 dropped because of collinearity
      begin with full model
p = 0.9632 >= 0.1000 removing illw2
p = 0.8198 >= 0.1000 removing bf14
p = 0.7254 >= 0.1000 removing b4Xd2
p = 0.5552 >= 0.1000 removing shrelaw2
p = 0.5003 >= 0.1000 removing bf40
p = 0.4569 >= 0.1000 removing bf7
p = 0.2462 >= 0.1000 removing bf1
p = 0.1474 >= 0.1000 removing bf6

```

Logistic regression

Number of obs = 363

LR chi2(5) = 149.39

Prob > chi2 = 0.0000

Log likelihood = -108.87292

Pseudo R2 = 0.4069

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0975313	.0188222	5.18	0.000	.0606406	.1344221
radhlw2	.0162388	.0058329	2.78	0.005	.0048066	.027671
shrelaw2Xd2	-.0116334	.0048733	-2.39	0.017	-.0211849	-.002082
avgcumdosew2	.9243072	.3378348	2.74	0.006	.2621633	1.586451
bf4	-.1705368	.0357567	-4.77	0.000	-.2406188	-.1004549
_cons	-6.899952	1.254724	-5.50	0.000	-9.359167	-4.440737

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	45	11	56
-	29	278	307
Total	74	289	363

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	60.81%
Specificity	$\Pr(- \sim D)$	96.19%
Positive predictive value	$\Pr(D +)$	80.36%
Negative predictive value	$\Pr(\sim D -)$	90.55%

False + rate for true ~D	$\Pr(+ \sim D)$	3.81%
False - rate for true D	$\Pr(- D)$	39.19%
False + rate for classified +	$\Pr(\sim D +)$	19.64%
False - rate for classified -	$\Pr(D -)$	9.45%

Correctly classified	88.98%
----------------------	--------

Logistic model for HP2probsoc, goodness-of-fit test

```

        number of observations =      363
number of covariate patterns =      362
        Pearson chi2(356) =      411.50
        Prob > chi2 =      0.0225

```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-183.570	Log-Lik Full Model:	-108.873
D(357):	217.746	LR(5):	149.394
		Prob > LR:	0.000
McFadden's R2:	0.407	McFadden's Adj R2:	0.374
Maximum Likelihood R2:	0.337	Cragg & Uhler's R2:	0.530
McKelvey and Zavoina's R2:	0.616	Efron's R2:	0.452
Variance of y*:	8.560	Variance of error:	3.290
Count R2:	0.890	Adj Count R2:	0.459
AIC:	0.633	AIC*n:	229.746
BIC:	-1886.556	BIC':	-119.922

```

665 .
666 . scalar ProbsocModFw2 = "none"

667 .
668 .
669 . title4 "H1 pt 2 wave 2 testing for mediators for males"

```

H1 pt 2 wave 2 testing for mediators for males

```

670 . * Male mediator dose social problem response models
671 .
672 .
673 .
674 . // age is a male mediator
675 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

676 . 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.)

677 .

```
678 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1693.4076
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933

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

	<u>AIC</u>	=	9.972986
Log likelihood = -1693.407647	<u>BIC</u>	=	419831.3

radhlw2	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128	
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522	

```
679 . glm HP2probsoc radhlw2 if gender==1,fam(bin) irls link(probit) scale(dev)
```

```
Iteration 1: deviance = 226.5911
Iteration 2: deviance = 218.8478
Iteration 3: deviance = 218.3822
Iteration 4: deviance = 218.3787
Iteration 5: deviance = 218.3787
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 218.378733	(1/df) Deviance	=	.6460909
Pearson = 326.2667817	(1/df) Pearson	=	.9652863

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

	BIC	=	-1751.805
--	-----	---	-----------

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0149459	.0022581	6.62	0.000	.0105201	.0193717
_cons	-2.034921	.1640547	-12.40	0.000	-2.356462	-1.71338

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

680 .

681 . glm shjobw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1730.3274

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1550.634
Deviance = 524114.2615	(1/df) Deviance	=	1550.634
Pearson = 524114.2615	(1/df) Pearson	=	1550.634
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	AIC	=	10.19016
Log likelihood = -1730.327396	BIC	=	522144.1

shjobw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.7146559	.8541028	0.84	0.403	-.9593549	2.388667
_cons	49.09491	2.288162	21.46	0.000	44.61019	53.57962

682 . glm HP2probsoc shjobw2 if gender==1,fam(bin) irls link(probit) scale(dev)

Iteration 1: deviance = 241.5668
Iteration 2: deviance = 238.4954
Iteration 3: deviance = 238.438
Iteration 4: deviance = 238.438
Iteration 5: deviance = 238.438

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 238.4379517	(1/df) Deviance	=	.7054377
Pearson = 344.7520389	(1/df) Pearson	=	1.019976

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

[Bernoulli]
 [Probit]

BIC = -1731.746

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw2	.0079142	.0019981	3.96	0.000	.003998	.0118303
_cons	-1.622345	.1436613	-11.29	0.000	-1.903915	-1.340774

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

683 .

684 . glm shrelaw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1686.1612

Generalized linear models

Optimization : ML

No. of obs = 339

Residual df = 337

Scale parameter = 1231.384

Deviance = 414976.438

(1/df) Deviance = 1231.384

Pearson = 414976.438

(1/df) Pearson = 1231.384

Variance function: $V(u) = 1$

[Gaussian]

Link function : $g(u) = u$

[Identity]

Log likelihood = -1686.16125

AIC = 9.959653

BIC = 413013.1

shrelaw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.6230115	.7612097	0.82	0.413	-.868932	2.114955
_cons	26.21356	2.042278	12.84	0.000	22.21077	30.21635

```
685 . glm HP2probsoc shrelaw2 if gender==1,fam(bin) irls link(probit) scale(dev)
```

```
Iteration 1:  deviance = 247.6569
Iteration 2:  deviance = 246.6168
Iteration 3:  deviance = 246.614
Iteration 4:  deviance = 246.614
```

```
Generalized linear models                                No. of obs      =       339
Optimization      :  MQL Fisher scoring                 Residual df     =       337
                  (IRLS EIM)                          Scale parameter =         1
Deviance          = 246.6140476                        (1/df) Deviance =  .7317924
Pearson           = 341.2333206                        (1/df) Pearson  =  1.012562
```

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

```
BIC = -1716.748
```

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw2	.0043873	.0020436	2.15	0.032	.0003819	.0083926
_cons	-1.301708	.0997015	-13.06	0.000	-1.497119	-1.106297

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

```
686 .
687 . glm radhlw2 shjobw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1684.8126
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  ML                                 Residual df     =       337
Scale parameter = 1189.928
Deviance          = 401005.7796                        (1/df) Deviance = 1189.928
Pearson           = 401005.7796                        (1/df) Pearson  = 1189.928
```

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

```
AIC = 9.92831
BIC = 399041.4
Log likelihood = -1684.812637
```

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw2	.1991928	.0476483	4.18	0.000	.1058038	.2925817
avgcumdosew2	1.078018	.7489714	1.44	0.150	-.3899386	2.545975
_cons	35.85263	3.080591	11.64	0.000	29.81478	41.89047

```

688 . glm HP2probsoc shjobw2 avgcumdosew2 shjobw2Xd2 radhlw2 if gender==1,fam(bin)
> ///
> irls scale(dev) link(probit)

```

```

Iteration 1:  deviance = 220.8951
Iteration 2:  deviance = 210.5288
Iteration 3:  deviance = 208.6963
Iteration 4:  deviance = 208.3623
Iteration 5:  deviance = 208.3262
Iteration 6:  deviance = 208.3254
Iteration 7:  deviance = 208.3254
Iteration 8:  deviance = 208.3254

```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	335
(IRLS EIM)	Scale parameter	=	1
Deviance = 208.3253662	(1/df) Deviance	=	.6218668
Pearson = 303.1137306	(1/df) Pearson	=	.9048171

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

BIC = -1744.371

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw2	.0028813	.0028376	1.02	0.310	-.0026803	.008443
avgcumdosew2	-.4311286	.2898739	-1.49	0.137	-.999271	.1370138
shjobw2Xd2	.0049627	.0030471	1.63	0.103	-.0010095	.0109349
radhlw2	.0146066	.0023358	6.25	0.000	.0100285	.0191848
_cons	-2.096189	.2712131	-7.73	0.000	-2.627757	-1.564621

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

```

689 .
690 . scalar ProbsocMedMw2 = "age"

691 .
692 . title4 "H1 pt2 wave 2 HP2probsoc female mediator tests"

```

```

H1 pt2 wave 2 HP2probsoc female mediator tests

```

```

693 .
694 . // age is a possible female mediator
695 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

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

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

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

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

```

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

[Bernoulli]
 [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.)

697 .

698 . // radhlw2 is a possible female mediator

699 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1791.2233

Generalized linear models

Optimization : ML

Deviance = 410661.5604

Pearson = 410661.5604

No. of obs = 363

Residual df = 361

Scale parameter = 1137.567

(1/df) Deviance = 1137.567

(1/df) Pearson = 1137.567

Variance function: $V(u) = 1$

Link function : $g(u) = u$

[Gaussian]

[Identity]

Log likelihood = -1791.223306

AIC = 9.880018

BIC = 408533.7

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

```
700 . glm HP2probsoc radhlw2 if gender==2,fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 335.706
Iteration 2:  deviance = 333.7569
Iteration 3:  deviance = 333.7467
Iteration 4:  deviance = 333.7467
Iteration 5:  deviance = 333.7467
```

```
Generalized linear models          No. of obs      =       363
Optimization      : ML Fisher scoring      Residual df    =       361
                    (IRLS EIM)              Scale parameter =        1
Deviance          = 333.7467432          (1/df) Deviance =  .9245062
Pearson           = 373.5069806          (1/df) Pearson  =  1.034645
```

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

```
BIC = -1794.133
```

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0135849	.002393	5.68	0.000	.0088947	.0182751
_cons	-1.729418	.1840212	-9.40	0.000	-2.090093	-1.368743

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

```
701 .
702 . // bf4 is a possible female mediator
703 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

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

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

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

```
AIC = 6.121754
BIC = 7450.466
Log likelihood = -1109.098281
```

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

```
704 . 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      :  ML 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					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
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.)

```

705 .
706 . glm shrelaw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1767.2727**

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
		Scale parameter	=	996.9369
Deviance	= 359894.211	(1/df) Deviance	=	996.9369
Pearson	= 359894.211	(1/df) Pearson	=	996.9369
Variance function: $V(u) = 1$		[Gaussian]		
Link function : $g(u) = u$		[Identity]		
		<u>AIC</u>	=	9.748059
Log likelihood = -1767.272695		<u>BIC</u>	=	357766.3

shrelaw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.945314	1.20186	1.62	0.106	-.4102891	4.300917
_cons	22.64351	1.976084	11.46	0.000	18.77046	26.51657

```

707 . glm HP2probsoc shrelaw2 bf4 if gender==2,fam(bin) irls scale(dev) link(probi
> t)

```

Iteration 1: deviance = **289.2064**
 Iteration 2: deviance = **281.788**
 Iteration 3: deviance = **281.4059**
 Iteration 4: deviance = **281.4028**
 Iteration 5: deviance = **281.4028**
 Iteration 6: deviance = **281.4028**

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	360
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 281.4028288	(1/df) Deviance	=	.7816745
Pearson	= 310.3983516	(1/df) Pearson	=	.8622176
Variance function: $V(u) = u*(1-u)$		[Bernoulli]		
Link function : $g(u) = \text{invnorm}(u)$		[Probit]		
		BIC	=	-1840.582

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw2	-.0081327	.0026244	-3.10	0.002	-.0132764	-.002989
bf4	-.1491375	.015739	-9.48	0.000	-.1799854	-.1182895
_cons	.6945159	.1749292	3.97	0.000	.351661	1.037371

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

```

708 .
709 .
710 . // shjobw2Xd2 is almost significant but not quite
711 . glm radhlw2 shjobw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1791.1332**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	360
	Scale parameter	=	1140.16
Deviance = 410457.7613	(1/df) Deviance	=	1140.16
Pearson = 410457.7613	(1/df) Pearson	=	1140.16

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

	<u>AIC</u>	=	9.885031
Log likelihood = -1791.133211	<u>BIC</u>	=	408335.8

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw2	-.0191223	.0452294	-0.42	0.672	-.1077704	.0695258
avgcumdosew2	3.347309	1.2897	2.60	0.009	.819544	5.875074
_cons	57.93542	3.14326	18.43	0.000	51.77474	64.09609

```

712 . glm HP2probsoc shjobw2 avgcumdosew2 shjobw2Xd2 if gender==2,fam(bin) irls s
    > cale(dev) link(probit)

```

```

Iteration 1:  deviance =  337.4422
Iteration 2:  deviance =  332.2358
Iteration 3:  deviance =  329.0807
Iteration 4:  deviance =  328.8969
Iteration 5:  deviance =  328.895
Iteration 6:  deviance =  328.895
Iteration 7:  deviance =  328.895

```

```

Generalized linear models                                No. of obs      =       363
Optimization      :  ML Fisher scoring                 Residual df     =       359
                   (IRLS EIM)                          Scale parameter =         1
Deviance          =  328.8950257                        (1/df) Deviance =  .9161421
Pearson           =  356.7664651                        (1/df) Pearson  =  .9937785

```

```

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

```

```

BIC = -1787.196

```

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
shjobw2	.0053961	.0034194	1.58	0.115	-.0013058	.0120979
avgcumdosew2	1.437383	.3964978	3.63	0.000	.6602614	2.214504
shjobw2Xd2	-.0121765	.0040881	-2.98	0.003	-.0201891	-.004164
_cons	-1.737153	.2989256	-5.81	0.000	-2.323036	-1.151269

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

```

713 .
714 . scalar ProbsocMedFw2 = "age bf4 radhlw2"
715 .

```

```

716 .
717 . * male hp2spM w2 mediators: age
718 . * dose is not significant main effect for males
719 . * female hp2spF w2 mediators: age radhlw2
720 . * dose is not sig main effect for males
721 .
722 . scalar SigDoseProbsocMw2 = "no"

723 .
724 .
725 .
726 . title4 "3. Matrix summary for H1 pt2 wave 2 HP2probsoc Impact"

```

```

3. Matrix summary for H1 pt2 wave 2 HP2probsoc Impact

```

```

727 .      matrix define  spMw2 = J(1,8, 0)

728 .      matrix define  spFw2 = J(1,8, 0)

729 . matrix colnames  spMw2=  hypnum ptnum wave gender medsig numMA sig numModsig
    > numMed

730 . matrix colnames  spFw2=  hypnum ptnum wave gender medsig numMA sig numModsig
    > numMed

731 .
732 .      matrix define  spMw2= (1, 2, 3, 1, 0, 4, 0, 1 )

733 .      matrix define  spFw2= (1, 2, 3, 2, 1, 5, 0, 3 )

734 .      matrix rowname  spMw2 =  spMw2

735 .      matrix rowname  spFw2 =  spFw2

736 .      matlist  spMw2

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
> 4	spMw2	1	2	3	1	0	
		0	1				

```
737 .      matlist  spFw2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	spFw2	1	2	3	2	1	
> 5	0	3					

```
738 .      matrix define H1pt2w2 = (  wkMw2 \  wkFw2 \  hmcrMw2 \  hmcrFw2 \  s
> pMw2 \  spFw2 )
```

```
739 .
```

```
740 .      matlist H1pt2w2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	2	1	0	
> 2	0	2					
	r1	1	2	2	2	0	
> 1	0	2					
	r1	1	2	3	1	0	
> 1	0	1					
	r1	1	2	3	2	1	
> 1	0	2					
	spMw2	1	2	3	1	0	
> 4	0	1					
	spFw2	1	2	3	2	1	
> 5	0	3					

```
741 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed
```

```
742 .      matrix rownames H1pt2w2 =   wkMw2 wkFw2 hmcrMw2 hmcrFw2 socprbMw2 socprb
> Fw2
```

```
743 .      matlist H1pt2w2
```

		hypnum	ptnum	wave	gender	medsig	numMAasi
> g	numModsig	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2	0	2					
	wkFw2	1	2	2	2	0	
> 1	0	2					
	hmcrMw2	1	2	3	1	0	
> 1	0	1					
	hmcrFw2	1	2	3	2	1	
> 1	0	2					
	socprbMw2	1	2	3	1	0	
> 4	0	1					
	socprbFw2	1	2	3	2	1	
> 5	0	3					

```
744 .
```

```
745 .
```

```
746 . *xx significant dose effect for females
```

```
747 . scalar ProbsocModFw2 = "none"
```

```
748 . *xx no female moderators for Dose Social problem impact relationship
```

```
749 . scalar list
```

```

MainEffPrbsocMw2 = age radhlw2 shjobw2
MainEffhmcrFw2 = age
hmcrMedFw2 = age bf4
MainEffwkFw2 = age
MainEffwkMw2 = age
inthobMedMw2 = age
inthobMw2 = age
sxlifeMedMw2 = age illw2
SigDoseSxlifeFw2 = no
MainEffsxlifeFw2 = age radhlw2 bf4 bf4m
PrbfmhmModMw2 = none
MainEffProbSocFw2 = age radhlw2 avgcumdosew2 bf4
hmcrModMw2 = none
MainEffhmcrMw2 = age
    wkMedFw2 = age b4
    wkMedMw2 = age bf4
MainEffVactnMw2 = age radhlw2
MainEffsxlifeMw2 = age bf4 bf40 shjobw2 shrelaw2 radhlw2
MainEffPrbfmhmMw2 = bf4 bf6 bf7
ProbsocMedFw2 = age bf4 radhlw2
hmcareMedFw2 = age bf4
    WkhmcrMw2 = age b4
MainEffhmcrw2 = age

```

```

hmcrModFw2 = none
SigDoseHmcrFw2 = yes
NumhmcrModMw2 = none
SigDosehmcrMw2 = no
SigdosehmcrFw2 = yes
hmcrMedMw2 = age ageXillw2
SigDosehmcrFw2 = no
MainEffhmcareMw2 = age
    WkMedMw2 = age ageXillw2
    wkMedFw3 = radhlw3 age ageXillw3 bf40 bf4m bf1
VactnMedFw2 = age illw2 radhlw2
VactnMedMw2 = age illw2
VacatnModFw2 = none
MainEffVactnFw2 = age radhlw2 bf7m
SigDoseVactnFw2 = no
VactnModMw2 = none
vactnModMw2 = none
SigDoseVactnMw2 = no
inthobMedFw2 = age bf4 illw2 bf4m
InthbModFw2 = none
MainEffInthbFw2 = age radhlw2 bf4
SigdoseInthbFw2 = no
InthbModMw2 = none
MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
MainEffMw2 = radhlw2 bf4 bf40
SigdoseMEinthob = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
SxLifeModFw2 = no
sxlifeModFw2 = none
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf4 bf6 bf7
ProbsocMedMw2 = age
ProbsocModFw2 = none
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
PrbsocModMw2 = none
SigdoseMw2 = none
hmcareMedMw2 = age

```

```

hmcareModFw2 = none
MainEffhmcarew2 = age
SigdoseHmcareFw2 = no
hmcareModMw2 = none
SigDoseHmcareMw2 = no
NameMedMw2 = age ageXillw2
  NumModMw2 = none
SigDosehmcareMw2 = no
SigDoseWKMw2 = no
  WkMedFw2 = age bf4
  WkModFw2 = none
  WKModMw2 = none
SigDoseWkMw2 = no
SigDoseWkFw2 = no
SigDoseFw2 = no
  wkModFw2 = none
  wkModMw2 = none
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

```



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

```
755 . forvalues j = 2/2 {
      2. set more off
      3.
756 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
757 .   foreach var in HP2pbfhm {
      5.       forvalues k=1/2 {
      6. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      7.
758 . 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.
759 .   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 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

educ7	byte	%8.0g		specialist/master's degree
marrw21	byte	%8.0g		educ==7. doctor of science/phd
marrw22	byte	%8.0g		marrw2==1. single
marrw23	byte	%8.0g		marrw2==2. cohabitating
marrw24	byte	%8.0g		marrw2==3. married
marrw25	byte	%8.0g		marrw2==4. separated
marrw26	byte	%8.0g		marrw2==5. divorced
inclw2	double	%15.0g	LABJ	marrw2==6. widowed
				Income is not sufficient for
				basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for
				basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics
				plus extra purchases/savings
				in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably
				afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiw1 - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt -
				1.01635E-007)

Full main model for HP2pbfhm for wave= 2

chunk 5 H1 test:Gender= 1 model Wave = 2 for HP2probsoc

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 12 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ5w2 != 0 predicts failure perfectly

 occ5w2 dropped and 17 obs not used

note: occ6w2 != 0 predicts failure perfectly

 occ6w2 dropped and 4 obs not used

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 43 obs not used

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

note: marrw25 != 0 predicts failure perfectly
marrw25 dropped and 4 obs not used

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

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

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 2 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: bf15 omitted because of collinearity

Logistic regression	Number of obs	=	201
	LR chi2(32)	=	57.01
	Prob > chi2	=	0.0042
Log likelihood = -38.789787	Pseudo R2	=	0.4236

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0838902	.0451044	1.86	0.063	-.0045127	.1722932
_Ieduc_2	0	(omitted)				
_Ieduc_3	-1.068513	.9797271	-1.09	0.275	-2.988743	.851717
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.7464993	1.30613	-0.57	0.568	-3.306468	1.813469
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	1.365472	9.739165	0.14	0.888	-17.72294	20.45389
occ2w2	.1388058	9.737518	0.01	0.989	-18.94638	19.22399
occ3w2	1.99317	9.743118	0.20	0.838	-17.10299	21.08933
occ4w2	2.351827	9.813506	0.24	0.811	-16.88229	21.58595
occ5w2	0	(omitted)				
occ6w2	0	(omitted)				

occ7w2	.8526169	9.853293	0.09	0.931	-18.45948	20.16472
occ8w2	0	(omitted)				
marrw21	9.450183	1628.316	0.01	0.995	-3181.99	3200.891
marrw22	0	(omitted)				
marrw23	8.041239	1628.316	0.00	0.996	-3183.4	3199.482
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inclw2	0	(omitted)				
inc2w2	-.2472615	9.778068	-0.03	0.980	-19.41192	18.9174
inc3w2	.4803685	9.779356	0.05	0.961	-18.68682	19.64755
inc4w2	0	(omitted)				
radhlw2	.0219991	.0174949	1.26	0.209	-.0122902	.0562884
havmil	-.0118024	.0110278	-1.07	0.285	-.0334164	.0098117
avgcumdosew2	-.108206	.7718766	-0.14	0.889	-1.621056	1.404644
bf1	-.0239769	.0247822	-0.97	0.333	-.0725492	.0245953
bf4	-.1619124	.088191	-1.84	0.066	-.3347635	.0109388
bf6	.0726065	.0265235	2.74	0.006	.0206214	.1245916
bf7	.5947613	.2273662	2.62	0.009	.1491317	1.040391
bf14	-.0000762	.0001284	-0.59	0.553	-.0003279	.0001756
bf15	0	(omitted)				
bf40	.1113503	.2734738	0.41	0.684	-.4246485	.6473491
deaw2	.5485131	.536457	1.02	0.307	-.5029234	1.59995
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	.185387	1.066161	0.17	0.862	-1.904251	2.275025
movew2	-.6539417	1.506102	-0.43	0.664	-3.605848	2.297965
illw2	1.606215	.6542566	2.46	0.014	.3238954	2.888534
shfamw2	-.0092438	.0132973	-0.70	0.487	-.0353061	.0168184
shhlw2	-.031707	.0186076	-1.70	0.088	-.0681771	.0047632
shjobw2	.0258976	.0158492	1.63	0.102	-.0051662	.0569614
shrelaw2	-.0153159	.0142321	-1.08	0.282	-.0432103	.0125785
suprtw2	-.0315277	.0143652	-2.19	0.028	-.059683	-.0033724
suchrw2	.0165746	.0112144	1.48	0.139	-.0054051	.0385544
havmilsq	.0000128	.0000121	1.06	0.291	-.000011	.0000367
_cons	-18.46331	1628.32	-0.01	0.991	-3209.912	3172.985

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	6	2	8
-	15	178	193
Total	21	180	201

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	28.57%
Specificity	$\Pr(- \sim D)$	98.89%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	92.23%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.11%
False - rate for true D	$\Pr(- D)$	71.43%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	7.77%
Correctly classified		91.54%

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      201
number of covariate patterns =    201
    Pearson chi2(168) =      94.58
        Prob > chi2 =      1.0000
  
```

Measures of Fit for **logistic** of HP2pbfhm

Log-Lik Intercept Only:	-67.297	Log-Lik Full Model:	-38.790
D(152):	77.580	LR(32):	57.015
		Prob > LR:	0.004
McFadden's R2:	0.424	McFadden's Adj R2:	-0.305
Maximum Likelihood R2:	0.247	Cragg & Uhler's R2:	0.506
McKelvey and Zavoina's R2:	0.804	Efron's R2:	0.348
Variance of y*:	16.822	Variance of error:	3.290
Count R2:	0.915	Adj Count R2:	0.190
AIC:	0.874	AIC*n:	175.580
BIC:	-728.523	BIC':	112.691

Full main model for HP2pbfhm for wave= 2

chunk 5 H1 test:Gender= 2 model Wave = 2 for HP2pbfhm

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

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

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

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

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

note: movew2 != 0 predicts failure perfectly
movew2 dropped and 39 obs not used

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf15 omitted because of collinearity
convergence not achieved

Logistic regression	Number of obs	=	291
	LR chi2(39)	=	121.44
	Prob > chi2	=	0.0000
Log likelihood = -67.950854	Pseudo R2	=	0.4719

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0675647	.0282471	2.39	0.017	.0122015	.1229279
_Ieduc_2	22.46198	4.286253	5.24	0.000	14.06108	30.86288
_Ieduc_3	22.06025	4.212008	5.24	0.000	13.80487	30.31564
_Ieduc_4	22.4092	4.348301	5.15	0.000	13.88669	30.93171
_Ieduc_5	22.32965	4.28528	5.21	0.000	13.93065	30.72864
_Ieduc_6	22.02862	4.22306	5.22	0.000	13.75158	30.30567
_Ieduc_7	21.12883	.	.	.	.	.
_Ieduc_8	0	(omitted)				
occ1w2	.9568844	2.829891	0.34	0.735	-4.5896	6.503369
occ2w2	-2.026671	3.019495	-0.67	0.502	-7.944772	3.891431
occ3w2	1.405631	2.856151	0.49	0.623	-4.192322	7.003584
occ4w2	-1.270684	3.036271	-0.42	0.676	-7.221665	4.680297
occ5w2	2.733135	3.099019	0.88	0.378	-3.340831	8.8071
occ6w2	0	(omitted)				
occ7w2	2.390639	2.797142	0.85	0.393	-3.091658	7.872935
occ8w2	1.799797	3.171082	0.57	0.570	-4.415409	8.015004
marrw21	1.863442	1.565893	1.19	0.234	-1.205651	4.932536
marrw22	0	(omitted)				
marrw23	1.299753	1.073276	1.21	0.226	-.8038291	3.403334
marrw25	1.783742	1.600693	1.11	0.265	-1.353558	4.921042
marrw26	0	(omitted)				
inc1w2	-1.338762	2.877886	-0.47	0.642	-6.979314	4.301791
inc2w2	.7251666	2.789285	0.26	0.795	-4.741732	6.192065
inc3w2	.4037645	2.828422	0.14	0.886	-5.13984	5.947369
inc4w2	0	(omitted)				
radhlw2	.0119256	.0102886	1.16	0.246	-.0082396	.0320909
havmil	-.0040139	.0172972	-0.23	0.816	-.0379157	.0298879

avgcumdosew2	.2722171	.2230232	1.22	0.222	-.1649004	.7093346
bf1	-.0267246	.0134298	-1.99	0.047	-.0530465	-.0004027
bf4	-.3567161	.0758997	-4.70	0.000	-.5054767	-.2079554
bf6	.0040524	.0115093	0.35	0.725	-.0185053	.0266102
bf7	-.087478	.1503624	-0.58	0.561	-.382183	.2072269
bf14	-.0003779	.0001483	-2.55	0.011	-.0006686	-.0000872
bf15	0	(omitted)				
bf40	-.3388161	.1424322	-2.38	0.017	-.6179782	-.0596541
deaw2	-.0547509	.2551957	-0.21	0.830	-.5549253	.4454235
dvcew2	-1.224029	2.015285	-0.61	0.544	-5.173916	2.725858
sepaw2	0	(omitted)				
accdw2	-2.829263	1.402671	-2.02	0.044	-5.578447	-.0800779
movew2	0	(omitted)				
illw2	.0637667	.2827466	0.23	0.822	-.4904064	.6179399
shfamw2	.0166332	.00908	1.83	0.067	-.0011633	.0344296
shhlw2	.0127805	.0100076	1.28	0.202	-.006834	.0323949
shjobw2	-.0073866	.0092188	-0.80	0.423	-.0254551	.0106818
shrelaw2	-.0222876	.0112977	-1.97	0.049	-.0444307	-.0001445
suprtw2	-.0213951	.0081927	-2.61	0.009	-.0374524	-.0053378
suchrw2	-.0010257	.0080813	-0.13	0.899	-.0168647	.0148133
havmilsq	-6.28e-06	.0000546	-0.12	0.908	-.0001132	.0001006
_cons	-23.95744	5.116815	-4.68	0.000	-33.98621	-13.92866

Note: 2 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	27	8	35
-	20	236	256
Total	47	244	291

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	57.45%
Specificity	$\Pr(- \sim D)$	96.72%
Positive predictive value	$\Pr(D +)$	77.14%
Negative predictive value	$\Pr(\sim D -)$	92.19%
False + rate for true ~D	$\Pr(+ \sim D)$	3.28%
False - rate for true D	$\Pr(- D)$	42.55%
False + rate for classified +	$\Pr(\sim D +)$	22.86%
False - rate for classified -	$\Pr(D -)$	7.81%

Correctly classified 90.38%

Logistic model for HP2pbfhm, goodness-of-fit test

```
number of observations = 291
number of covariate patterns = 291
Pearson chi2(250) = 231.07
Prob > chi2 = 0.7993
```

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

Log-Lik Intercept Only:	-128.671	Log-Lik Full Model:	-67.951
D(242):	135.902	LR(39):	121.440
		Prob > LR:	0.000
Mcfadden's R2:	0.472	Mcfadden's Adj R2:	0.091
Maximum Likelihood R2:	0.341	Cragg & Uhler's R2:	0.581
McKelvey and Zavoina's R2:	0.819	Efron's R2:	0.487
Variance of y*:	18.199	Variance of error:	3.290
Count R2:	0.904	Adj Count R2:	0.404
AIC:	0.804	AIC*n:	233.902
BIC:	-1237.043	BIC':	99.819

760 .

761 .

762 . title4 "Partly Trimmed male Wave 2 Dose => Problems with Family at home mod
> els"

Partly Trimmed male Wave 2 Dose => Problems with Family at home models

763 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

764 . logit HP2pbfhm age bf6 bf7 radhlw2 avgcumdosew2 shhlw2 shjobw2 suprtw2 ///
> havmilsq illw2 if gender==1, iterate(50)

```
Iteration 0: log likelihood = -81.506236
Iteration 1: log likelihood = -70.711736
Iteration 2: log likelihood = -65.560557
Iteration 3: log likelihood = -65.354395
Iteration 4: log likelihood = -65.353064
Iteration 5: log likelihood = -65.353062
```

Logistic regression	Number of obs	=	340
	LR chi2(10)	=	32.31
	Prob > chi2	=	0.0004
Log likelihood = -65.353062	Pseudo R2	=	0.1982

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0370609	.0212772	1.74	0.082	-.0046417	.0787635
bf6	.0345573	.0133394	2.59	0.010	.0084125	.0607022
bf7	.2745069	.1197775	2.29	0.022	.0397473	.5092666
radhlw2	.0100781	.0082635	1.22	0.223	-.006118	.0262742
avgcumdosew2	-.1562252	.2515535	-0.62	0.535	-.649261	.3368105
shhlw2	-.0068707	.0086681	-0.79	0.428	-.0238598	.0101185
shjobw2	.0042909	.0081914	0.52	0.600	-.0117638	.0203457
suprtw2	-.0056613	.0058911	-0.96	0.337	-.0172077	.0058851
havmilsq	-1.23e-06	7.81e-06	-0.16	0.874	-.0000165	.0000141
illw2	.7484301	.3313945	2.26	0.024	.0989088	1.397951
_cons	-7.299944	1.469743	-4.97	0.000	-10.18059	-4.4193

```

765 .
766 . estat class

```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	1	1
-	22	317	339
Total	22	318	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	0.00%
Specificity	$\Pr(- \sim D)$	99.69%
Positive predictive value	$\Pr(D +)$	0.00%
Negative predictive value	$\Pr(\sim D -)$	93.51%
False + rate for true ~D	$\Pr(+ \sim D)$	0.31%
False - rate for true D	$\Pr(- D)$	100.00%
False + rate for classified +	$\Pr(\sim D +)$	100.00%
False - rate for classified -	$\Pr(D -)$	6.49%
Correctly classified		93.24%

767 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	340
number of covariate patterns =	338
Pearson chi2(327) =	250.44
Prob > chi2 =	0.9994

768 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-81.506	Log-Lik Full Model:	-65.353
D(329):	130.706	LR(10):	32.306
		Prob > LR:	0.000
McFadden's R2:	0.198	McFadden's Adj R2:	0.063
Maximum Likelihood R2:	0.091	Cragg & Uhler's R2:	0.238
McKelvey and Zavoina's R2:	0.404	Efron's R2:	0.093
Variance of y*:	5.524	Variance of error:	3.290
Count R2:	0.932	Adj Count R2:	-0.045
AIC:	0.449	AIC*n:	152.706
BIC:	-1787.017	BIC':	25.983

769 .

770 . title4 "trimmed male main effects wv 2" " Dose => Problems with Family at ho
> me models"

trimmed male main effects wv 2

771 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

772 . sw, pr(.1):logit HP2pbfhm age sepaw2 dvcew2 radhlw2 avgcumdosew2 bf4 bf6 bf7
> suprtw2 ///
> havmilsq illw2 if gender==1, iterate(50)
note: sepaw2 dropped because of estimability
note: dvcew2 dropped because of estimability
note: o.sepaw2 dropped because of estimability
note: o.dvcew2 dropped because of estimability
note: 10 obs. dropped because of estimability
begin with full model
p = 0.8936 >= 0.1000 removing havmilsq
p = 0.7469 >= 0.1000 removing avgcumdosew2
p = 0.6617 >= 0.1000 removing radhlw2
p = 0.3316 >= 0.1000 removing suprtw2
p = 0.2216 >= 0.1000 removing age

Logistic regression

Number of obs = 330

LR chi2(4) = 30.41

Prob > chi2 = 0.0000

Log likelihood = -65.61942

Pseudo R2 = 0.1881

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf6	.0392413	.01226	3.20	0.001	.0152122	.0632704
bf7	.2697216	.1148207	2.35	0.019	.0446772	.494766
illw2	.5624726	.330378	1.70	0.089	-.0850564	1.210002
bf4	-.1039323	.0416421	-2.50	0.013	-.1855494	-.0223153
_cons	-4.327314	1.14845	-3.77	0.000	-6.578234	-2.076394

773 .

774 . estat class

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	22	308	330
Total	22	308	330

Classified + if predicted Pr(D) >= .5

True D defined as HP2pbfhm != 0

Sensitivity	Pr(+ D)	0.00%
Specificity	Pr(- ~D)	100.00%
Positive predictive value	Pr(D +)	.%
Negative predictive value	Pr(~D -)	93.33%

False + rate for true ~D	Pr(+ ~D)	0.00%
False - rate for true D	Pr(- D)	100.00%
False + rate for classified +	Pr(~D +)	.%
False - rate for classified -	Pr(D -)	6.67%

Correctly classified	93.33%
----------------------	--------

775 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	330
number of covariate patterns =	157
Pearson chi2(152) =	131.86
Prob > chi2 =	0.8794

776 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-80.827	Log-Lik Full Model:	-65.619
D(325):	131.239	LR(4):	30.415
		Prob > LR:	0.000
McFadden's R2:	0.188	McFadden's Adj R2:	0.126
Maximum Likelihood R2:	0.088	Cragg & Uhler's R2:	0.227
McKelvey and Zavoina's R2:	0.353	Efron's R2:	0.106
Variance of y*:	5.085	Variance of error:	3.290
Count R2:	0.933	Adj Count R2:	0.000
AIC:	0.428	AIC*n:	141.239
BIC:	-1753.466	BIC':	-7.219

777 .

778 . scalar MainEffPrbfhmMw2 = "bf4 bf6 bf7"

779 . scalar SigDosePrbfhmMw2 = "no"

780 . // construction of moderators for male model

781 .

```
782 . foreach var in bf4 bf6 bf7 {  
      2.  cap gen `var'Xd2 = `var'*avgcumdosew2  
      3.  }
```

783 .

```

784 .
785 .
786 .
787 . *****
> **
788 . *-----chunk 6 continued -testing moderators and none found for males
789 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

790 .
791 .
792 . title4 "fully Trimmed male main effects wv 3" ///
> "Dose => Problems with Family at home models"

```

```
fully Trimmed male main effects wv 3
```

```

793 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

794 . logit HP2pbfhm age radhlw2 avgcumdosew2 ///
> bf6Xd2 bf7Xd2 if ///
> gender==1, iterate(50)

```

```

Iteration 0: log likelihood = -81.506236
Iteration 1: log likelihood = -73.447506
Iteration 2: log likelihood = -70.882142
Iteration 3: log likelihood = -69.255694
Iteration 4: log likelihood = -68.922279
Iteration 5: log likelihood = -68.919492
Iteration 6: log likelihood = -68.919491

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	25.17
	Prob > chi2	=	0.0001
Log likelihood = -68.919491	Pseudo R2	=	0.1544

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0386912	.0199545	1.94	0.053	-.0004189	.0778014
radhlw2	.0143508	.0076003	1.89	0.059	-.0005455	.0292471
avgcumdosew2	-3.388044	1.802017	-1.88	0.060	-6.919932	.1438441
bf6Xd2	.0367575	.0198745	1.85	0.064	-.0021958	.0757109
bf7Xd2	.3054727	.1764719	1.73	0.083	-.0404059	.6513514
_cons	-5.00095	1.200256	-4.17	0.000	-7.353408	-2.648492

Note: 3 failures and 0 successes completely determined.

```
795 .
796 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	22	318	340
Total	22	318	340

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	$\Pr(\sim D -)$	93.53%
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 -	$\Pr(D -)$	6.47%
Correctly classified		93.53%

```
797 . estat gof
```

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    329
    Pearson chi2(323) =    290.81
        Prob > chi2 =      0.9005
```

798 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-81.506	Log-Lik Full Model:	-68.919
D(334):	137.839	LR(5):	25.173
		Prob > LR:	0.000
McFadden's R2:	0.154	McFadden's Adj R2:	0.081
Maximum Likelihood R2:	0.071	Cragg & Uhler's R2:	0.187
McKelvey and Zavoina's R2:	0.903	Efron's R2:	0.079
Variance of y*:	33.925	Variance of error:	3.290
Count R2:	0.935	Adj Count R2:	0.000
AIC:	0.441	AIC*n:	149.839
BIC:	-1809.029	BIC':	3.971

799 .

800 . scalar SigDosePrbfmhmMw2 = "no"

801 . scalar PrbfmhmModMw2 = "none"

802 . scalar MainEffPrbfmhmMw2= "bf4 bf6 bf7"

803 . * 3 main effects signif no main effect for dose for males

804 .

805 .

806 . *-----Chunk 6 continued -testing meditors for females

807 . title4 "Partly Trimmed female Wave 2" "Dose => Problems with Family at home
> models"

Partly Trimmed female Wave 2

808 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

809 . logit HP2pbfhm age radhlw2 avgcumdosew2 bf4 if gender==2, iterate(50)

Iteration 0: log likelihood = **-139.89675**
Iteration 1: log likelihood = **-113.0036**
Iteration 2: log likelihood = **-107.10312**
Iteration 3: log likelihood = **-106.98442**
Iteration 4: log likelihood = **-106.98403**
Iteration 5: log likelihood = **-106.98403**

Logistic regression

Log likelihood = **-106.98403**

Number of obs	=	363
LR chi2(4)	=	65.83
Prob > chi2	=	0.0000
Pseudo R2	=	0.2353

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0557545	.0170818	3.26	0.001	.0222747	.0892342
radhlw2	.0108772	.0060404	1.80	0.072	-.0009617	.0227161
avgcumdosew2	-.0049664	.0969934	-0.05	0.959	-.19507	.1851373
bf4	-.1657135	.0368332	-4.50	0.000	-.2379053	-.0935217
_cons	-4.323335	1.125843	-3.84	0.000	-6.529946	-2.116724

```
810 .
811 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	9	6	15
-	38	310	348
Total	47	316	363

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	19.15%
Specificity	$\Pr(- \sim D)$	98.10%
Positive predictive value	$\Pr(D +)$	60.00%
Negative predictive value	$\Pr(\sim D -)$	89.08%

False + rate for true ~D	$\Pr(+ \sim D)$	1.90%
False - rate for true D	$\Pr(- D)$	80.85%
False + rate for classified +	$\Pr(\sim D +)$	40.00%
False - rate for classified -	$\Pr(D -)$	10.92%

Correctly classified	87.88%
----------------------	--------

812 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	363
number of covariate patterns =	361
Pearson chi2(356) =	363.32
Prob > chi2 =	0.3830

813 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-139.897	Log-Lik Full Model:	-106.984
D(358):	213.968	LR(4):	65.825
		Prob > LR:	0.000
McFadden's R2:	0.235	McFadden's Adj R2:	0.200
Maximum Likelihood R2:	0.166	Cragg & Uhler's R2:	0.309
McKelvey and Zavoina's R2:	0.390	Efron's R2:	0.216
Variance of y*:	5.395	Variance of error:	3.290
Count R2:	0.879	Adj Count R2:	0.064
AIC:	0.617	AIC*n:	223.968
BIC:	-1896.228	BIC':	-42.248

814 .

815 . scalar SigDosePrbfbhmFw2="no"

816 .

817 . *-----Chunk 6 continued -testing meditors for females

818 . title4 "More partly female Trimmed Wave 2" "Dose => Problems with Family at
> home models"

More partly female Trimmed Wave 2

819 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

```
820 . 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
Pseudo R2      =      0.2414
```

Log likelihood = **-106.12091**

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

```
821 .
```

```
822 . 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%**

823 . 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

824 . 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

825 .

826 .

827 . scalar MainEffPrbfmhmFw2 = "age bf4 bf40"

828 . * 3 significant main effects for females

829 . * no significant main effect for dose

830 .

831 . * constructing moderators

832 .

```

833 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd2 = `var'*avgcumdosew2
      3. }

834 .
835 .
836 . title4 "testing female moderator effects:  no moderator effects for females"

```

```

testing female moderator effects:  no moderator effects for females

```

```

837 .
838 . logit HP2pbfhm age bf4 bf40 ageXd2 bf4Xd2 bf40Xd2 if gender==2, iterate(50)

```

```

Iteration 0:  log likelihood = -139.89675
Iteration 1:  log likelihood = -111.91159
Iteration 2:  log likelihood = -105.8511
Iteration 3:  log likelihood = -104.97326
Iteration 4:  log likelihood = -104.94985
Iteration 5:  log likelihood = -104.9498
Iteration 6:  log likelihood = -104.9498

```

Logistic regression	Number of obs	=	363
	LR chi2(6)	=	69.89
	Prob > chi2	=	0.0000
Log likelihood = -104.9498	Pseudo R2	=	0.2498

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.057978	.018048	3.21	0.001	.0226046	.0933514
bf4	-.2081538	.0505288	-4.12	0.000	-.3071884	-.1091193
bf40	-.0721876	.1339532	-0.54	0.590	-.334731	.1903558
ageXd2	.006707	.0069963	0.96	0.338	-.0070055	.0204195
bf4Xd2	.0146354	.0371601	0.39	0.694	-.0581971	.087468
bf40Xd2	-.1308031	.1156271	-1.13	0.258	-.357428	.0958218
_cons	-3.176982	1.121456	-2.83	0.005	-5.374996	-.9789674

839 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

```

      number of observations =      363
number of covariate patterns =      359
      Pearson chi2(352) =      361.42
          Prob > chi2 =      0.3531

```

840 . estat class

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	14	4	18
-	33	312	345
Total	47	316	363

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	29.79%
Specificity	$\Pr(- \sim D)$	98.73%
Positive predictive value	$\Pr(D +)$	77.78%
Negative predictive value	$\Pr(\sim D -)$	90.43%
False + rate for true ~D	$\Pr(+ \sim D)$	1.27%
False - rate for true D	$\Pr(- D)$	70.21%
False + rate for classified +	$\Pr(\sim D +)$	22.22%
False - rate for classified -	$\Pr(D -)$	9.57%
Correctly classified		89.81%

841 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-139.897	Log-Lik Full Model:	-104.950
D(356):	209.900	LR(6):	69.894
		Prob > LR:	0.000
McFadden's R2:	0.250	McFadden's Adj R2:	0.200
Maximum Likelihood R2:	0.175	Cragg & Uhler's R2:	0.326
McKelvey and Zavoina's R2:	0.411	Efron's R2:	0.233
Variance of y*:	5.585	Variance of error:	3.290
Count R2:	0.898	Adj Count R2:	0.213
AIC:	0.617	AIC*n:	223.900
BIC:	-1888.508	BIC':	-34.527

842 .

843 . scalar PrbfmhmModFw2="none"

844 .

845 . *****
> ****

846 . *-----Chunk 6 continued testing mediating effects for Problems with fami
> ly

847 . * at home

848 .

849 . * age is a mediating effect for males for Dose=> problems with family at hom
> e

850 . 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)

851 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	147.6853
Deviance	= 49917.64009	(1/df) Deviance	=	147.6853
Pearson	= 49917.64009	(1/df) Pearson	=	147.6853
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]

Log likelihood	=	-1330.6004	<u>AIC</u>	=	7.838826
			<u>BIC</u>	=	47947.46

	OIM					
age	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
852 . glm HP2pbfhm age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 163.1004
Iteration 2:    deviance = 152.8997
Iteration 3:    deviance = 151.9532
Iteration 4:    deviance = 151.9347
Iteration 5:    deviance = 151.9347
Iteration 6:    deviance = 151.9347
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 151.9346518	(1/df) Deviance	=	.4495108
Pearson = 324.8005072	(1/df) Pearson	=	.9609482

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

BIC = -1818.249

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0296385	.0061334	4.83	0.000	.0176173	.0416597
_cons	-3.073816	.3430721	-8.96	0.000	-3.746225	-2.401407

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

```

853 .
854 . glm bf4  avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

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

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	24.7771
Deviance = 8374.659221	(1/df) Deviance	=	24.7771
Pearson = 8374.659221	(1/df) Pearson	=	24.7771
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	6.053662
Log likelihood = -1027.122509	<u>BIC</u>	=	6404.476

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

```

855 . 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.)

```

856 .
857 . * age is a mediating effect for females for Dose=> Problems with family at h
    > ome
858 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

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

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

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

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

```

859 . 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.)

```

860 .
861 . * bf4 is a mediating effect for females for Dose=> Problems with family at ho
    > me
862 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

```

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

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

                                          AIC              =   6.121754
Log likelihood    = -1109.098281           BIC              =   7450.466

```

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

```
863 . 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 : $g(u) = \text{invnorm}(u)$ [**Probit**]

BIC = -1899.281

HP2pbfhm	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.1229375	.0145262	-8.46	0.000	-.1514083	-.0944667
_cons	-.0739521	.1322299	-0.56	0.576	-.3331179	.1852138

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

```
864 .
```

```
865 .
```

```
866 . glm bf6 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1783.7385
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1091.609
Deviance = 394070.7897	(1/df) Deviance	=	1091.609
Pearson = 394070.7897	(1/df) Pearson	=	1091.609

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

	<u>AIC</u>	=	9.838779
Log likelihood = -1783.738453	<u>BIC</u>	=	391942.9

bf6	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.917643	1.257632	1.52	0.127	-.5472713	4.382557
_cons	53.39006	2.067783	25.82	0.000	49.33728	57.44284

```
867 . glm HP2pbfhm bf6 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 270.845
Iteration 2: deviance = 267.9149
Iteration 3: deviance = 267.8425
Iteration 4: deviance = 267.8424
Iteration 5: deviance = 267.8424
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 267.8424366	(1/df) Deviance	=	.7419458
Pearson = 362.9777402	(1/df) Pearson	=	1.005479

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

BIC = **-1860.037**

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf6	.0094515	.0024584	3.84	0.000	.0046331	.0142698
_cons	-1.703802	.1741973	-9.78	0.000	-2.045223	-1.362382

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

```
868 .
```

869 .

870 . glm bf7 avgcumdosew2 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = **-902.57713**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	8.503897
Deviance = 3069.906975	(1/df) Deviance	=	8.503897
Pearson = 3069.906975	(1/df) Pearson	=	8.503897
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	4.983896
Log likelihood = -902.5771339	<u>BIC</u>	=	942.0276

bf7	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.1298425	.1110016	-1.17	0.242	-.3474016	.0877166
_cons	1.052922	.1825074	5.77	0.000	.695214	1.41063

871 . glm HP2pbfhm bf7 if gender==2, fam(bin) irls scale(dev) link(probit)

Iteration 1: deviance = **277.1289**
 Iteration 2: deviance = **275.4145**
 Iteration 3: deviance = **275.2733**
 Iteration 4: deviance = **275.2711**
 Iteration 5: deviance = **275.2711**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 275.2710641	(1/df) Deviance	=	.7625237
Pearson = 362.9709778	(1/df) Pearson	=	1.00546
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	BIC	=	-1852.608

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf7	-.0808371	.0385299	-2.10	0.036	-.1563543	-.0053198
_cons	-1.081139	.0750775	-14.40	0.000	-1.228288	-.9339898

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

```

872 .
873 . scalar PrbfmhmMedMw2 = "age"

874 . scalar PrbfmhmMedFw2 = "age bf4"

875 . * Summary of dose=problems with family at home mediating effects
876 . * males mediators age 1
877 . * females mediators age and BSIsoma rescaled (bf4) 2
878 .
879 . title4 "4. Summary matrix for problems with family at home"

```

```

4. Summary matrix for problems with family at home

```

```

880 .     matrix define prbfamMw2 = J(1,8, 0)

881 .         matrix define prbfamFw2 = J(1,8, 0)

882 . matrix colnames prbfamMw2=  hypnum ptnum wave gender medsig numMA sig numMods
    > ig numMed

883 .         matrix colnames prbfamFw2=  hypnum ptnum wave gender medsig numMA sig
    > numModsig numMed

884 .     matrix define prbfamMw2= (1, 2, 3, 1, 0, 3, 0, 1 )

885 .         matrix define prbfamFw2= (1, 2, 3, 2, 0, 3, 0, 2)

```

```
886 .      matrix rowname prbfamMw2 = prbfamMw2
```

```
887 .      matrix rowname prbfamFw2 = prbfamFw2
```

```
888 .      matlist prbfamMw2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	prbfamMw2	1	2	3	1	0	
> 3	0	1					

```
889 .      matlist prbfamFw2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	prbfamFw2	1	2	3	2	0	
> 3	0	2					

```
890 .      matrix define H1pt2w2 = ( wkMw2 \ wkFw2 \ hmcrMw2 \ hmcrFw2 \ spMw2
> \ spFw2 \ prbfamMw2 \ prbfamFw2)
```

```
891 .
```

```
892 .      matlist H1pt2w2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	2	1	0	
> 2	0	2					
	r1	1	2	2	2	0	
> 1	0	2					
	r1	1	2	3	1	0	
> 1	0	1					
	r1	1	2	3	2	1	
> 1	0	2					
	spMw2	1	2	3	1	0	
> 4	0	1					
	spFw2	1	2	3	2	1	
> 5	0	3					
	prbfamMw2	1	2	3	1	0	
> 3	0	1					
	prbfamFw2	1	2	3	2	0	
> 3	0	2					

```

893 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

```

```

894 .      matrix rownames H1pt2w2 =   wkMw2 wkFw2 hmcrMw2 hmcrFw2 prbsocMw2 prbsoc
> Fw2 prbfhmMw2 prbfhmFw2

```

```

895 .      matlist H1pt2w2

```

		hypnum	ptnum	wave	gender	medsig	numMA sig
> g	numModsig	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2	0	2					
	wkFw2	1	2	2	2	0	
> 1	0	2					
	hmcrMw2	1	2	3	1	0	
> 1	0	1					
	hmcrFw2	1	2	3	2	1	
> 1	0	2					
	prbsocMw2	1	2	3	1	0	
> 4	0	1					
	prbsocFw2	1	2	3	2	1	
> 5	0	3					
	prbfhmMw2	1	2	3	1	0	
> 3	0	1					
	prbfhmFw2	1	2	3	2	0	
> 3	0	2					

```

896 .

```

```

897 .

```

```

898 .

```

```

899 . *****
> *****

```

```

900 . *-----Chunk 7   Dose==> problems with sex life impact

```

```

901 . * Chunk 7   General model for all part 2 of Nottingham Health Profile

```

```

902 .

```



```

908 . di _skip(4)
      10.
909 .
910 .      xi: logistic `var' age i.educ occ1w`j' -occ8w`j' ///
      >      marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j' -inc4w`j' /
      > //
      >      radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
      >      deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
      >      illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
      > chrw`j' ///
      >      havmilsq radhlw2 if gender==`k', coef difficult iterate(50
      > )
      11.          estat class
      12.          estat gof
      13.          fitstat
      14. }
      15. }
      16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996

```

bf1          float   %9.0g          bf1 = max(0, kzchorn - 40)
bf4          float   %9.0g          bf4 = max(0, 24 - BSIsoma)
bf9          float   %9.0g          bf9= max(0, 30 - shhlw1)
bf11         float   %9.0g          bf11= max(0, 20 - sufamw1)
bf4m         float   %9.0g          bf4m = max(0, 32 - BSIsoma)
bf15m        float   %9.0g          bf15m= max(0, 1 - icdxcnt) * bf2
bf30         float   %9.0g          bf30 = max(0, neiw1 - 85) * bf20
bf40         float   %9.0g          bf40 = max(0, icdxcnt -
                                     1.01635E-007)

```

```

*****
> *
*****
> *
*****
> *
*****
Full Nottingham Part 2 subscale models for male & females
> *
*****
Full main model for HP2sxlife for wave= 2
> *
*****
chunk 7 H1 test:Gender= 1 model Wave = 2 for HP2pbfhm
> *
*****
> *
*****
> *
*****
17 Jun 2012 10:08:29
> *
*****
> *
*****
> *

```

```

i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: _Ieduc_4 != 0 predicts failure perfectly
      _Ieduc_4 dropped and 12 obs not used

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

note: occ8w2 != 0 predicts failure perfectly
      occ8w2 dropped and 43 obs not used

```

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

note: marrw25 != 0 predicts failure perfectly
marrw25 dropped and 4 obs not used

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 3 obs not used

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

note: _Ieduc_8 omitted because of collinearity
note: bf15 omitted because of collinearity
note: radhlw2 omitted because of collinearity

Logistic regression	Number of obs	=	248
	LR chi2(38)	=	124.45
	Prob > chi2	=	0.0000
Log likelihood = -81.459667	Pseudo R2	=	0.4331

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.045416	.0245513	1.85	0.064	-.0027037	.0935357
_Ieduc_2	-.0646877	2.529828	-0.03	0.980	-5.02306	4.893684
_Ieduc_3	-.2043117	2.425172	-0.08	0.933	-4.957562	4.548938
_Ieduc_4	0	(omitted)				
_Ieduc_5	.5468814	2.47638	0.22	0.825	-4.306734	5.400497
_Ieduc_6	-.5396204	2.395021	-0.23	0.822	-5.233776	4.154535
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-.914781	4.041769	-0.23	0.821	-8.836503	7.006941
occ2w2	-1.085289	4.050896	-0.27	0.789	-9.024899	6.854322
occ3w2	-2.01676	4.099586	-0.49	0.623	-10.0518	6.018282
occ4w2	-1.281739	4.07837	-0.31	0.753	-9.275197	6.711719
occ5w2	-2.386463	4.187943	-0.57	0.569	-10.59468	5.821754
occ6w2	1.041656	4.356584	0.24	0.811	-7.497091	9.580403
occ7w2	-.2042994	4.128602	-0.05	0.961	-8.296212	7.887613
occ8w2	0	(omitted)				
marrw21	11.19923	1268.681	0.01	0.993	-2475.369	2497.767
marrw22	0	(omitted)				
marrw23	11.00787	1268.681	0.01	0.993	-2475.56	2497.576
marrw25	0	(omitted)				
marrw26	9.989133	1268.682	0.01	0.994	-2476.582	2496.56
inclw2	2.592204	4.16321	0.62	0.534	-5.567537	10.75195

inc2w2	3.029964	4.086266	0.74	0.458	-4.978969	11.0389
inc3w2	2.803138	4.089233	0.69	0.493	-5.211611	10.81789
inc4w2	0	(omitted)				
radhlw2	.0158792	.0090915	1.75	0.081	-.0019397	.0336982
havmil	-.0002765	.0085069	-0.03	0.974	-.0169497	.0163966
avgcumdosew2	-.0370642	.0826057	-0.45	0.654	-.1989685	.1248401
bf1	.0019651	.0129727	0.15	0.880	-.0234608	.0273911
bf4	-.2487796	.05911	-4.21	0.000	-.3646331	-.1329261
bf6	.0163867	.0108586	1.51	0.131	-.0048957	.0376692
bf7	.0671464	.105745	0.63	0.525	-.1401099	.2744028
bf14	-.0000488	.0000798	-0.61	0.541	-.0002053	.0001076
bf15	0	(omitted)				
bf40	.3417099	.1521463	2.25	0.025	.0435086	.6399112
deaw2	.0342021	.3561465	0.10	0.923	-.6638321	.7322364
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0684013	.5282538	-0.13	0.897	-1.10376	.9669571
movew2	.1688384	.5667796	0.30	0.766	-.9420292	1.279706
illw2	.2358444	.3235455	0.73	0.466	-.398293	.8699819
shfamw2	-.0126799	.0083767	-1.51	0.130	-.0290979	.0037381
shhlw2	-.01343	.0100141	-1.34	0.180	-.0330573	.0061973
shjobw2	.0172317	.0096379	1.79	0.074	-.0016582	.0361216
shrelaw2	-.0093206	.0085022	-1.10	0.273	-.0259847	.0073434
suprtw2	.0077123	.0077451	1.00	0.319	-.0074679	.0228925
suchrw2	.0029045	.0070402	0.41	0.680	-.0108941	.016703
havmilsq	-1.32e-06	.0000139	-0.10	0.924	-.0000286	.0000259
radhlw2	0	(omitted)				
_cons	-16.32451	1268.684	-0.01	0.990	-2502.9	2470.251

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	47	15	62
-	19	167	186
Total	66	182	248

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

Sensitivity	$\Pr(+ D)$	71.21%
Specificity	$\Pr(- \sim D)$	91.76%
Positive predictive value	$\Pr(D +)$	75.81%
Negative predictive value	$\Pr(\sim D -)$	89.78%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	8.24%
False - rate for true D	$\Pr(- D)$	28.79%
False + rate for classified +	$\Pr(\sim D +)$	24.19%
False - rate for classified -	$\Pr(D -)$	10.22%
Correctly classified		86.29%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations = **248**
 number of covariate patterns = **248**
 Pearson $\chi^2(209)$ = **320.07**
 Prob > χ^2 = **0.0000**

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-143.684	Log-Lik Full Model:	-81.460
D(198):	162.919	LR(38):	124.448
		Prob > LR:	0.000
McFadden's R2:	0.433	McFadden's Adj R2:	0.085
Maximum Likelihood R2:	0.395	Cragg & Uhler's R2:	0.575
McKelvey and Zavoina's R2:	0.701	Efron's R2:	0.489
Variance of y*:	11.005	Variance of error:	3.290
Count R2:	0.863	Adj Count R2:	0.485
AIC:	1.060	AIC*n:	262.919
BIC:	-928.740	BIC':	85.062

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0946676	.020348	4.65	0.000	.0547862	.1345489
_Ieduc_2	-12.06916	856.9725	-0.01	0.989	-1691.704	1667.566
_Ieduc_3	-10.96566	856.9724	-0.01	0.990	-1690.601	1668.669
_Ieduc_4	-10.2721	856.9727	-0.01	0.990	-1689.908	1669.364
_Ieduc_5	-11.78295	856.9726	-0.01	0.989	-1691.418	1667.853
_Ieduc_6	-10.87488	856.9725	-0.01	0.990	-1690.51	1668.76
_Ieduc_7	-10.54712	856.9809	-0.01	0.990	-1690.199	1669.105
_Ieduc_8	0	(omitted)				
occ1w2	-1.924676	1.67129	-1.15	0.249	-5.200344	1.350992
occ2w2	-1.071334	1.695639	-0.63	0.528	-4.394725	2.252058
occ3w2	-.4988122	1.696518	-0.29	0.769	-3.823926	2.826301
occ4w2	-.6837643	1.779367	-0.38	0.701	-4.171259	2.803731
occ5w2	-.8653809	1.874647	-0.46	0.644	-4.539621	2.80886
occ6w2	-1.70777	1.969995	-0.87	0.386	-5.568889	2.153348
occ7w2	-.9209399	1.641247	-0.56	0.575	-4.137725	2.295845
occ8w2	-.5235734	1.936624	-0.27	0.787	-4.319287	3.272141
marrw21	-.4474367	1.15873	-0.39	0.699	-2.718505	1.823632
marrw22	-.2713813	1.430959	-0.19	0.850	-3.07601	2.533247
marrw23	-.6859987	.8247327	-0.83	0.406	-2.302445	.9304478
marrw25	-1.534831	1.287976	-1.19	0.233	-4.059218	.9895558
marrw26	0	(omitted)				
inc1w2	.1793057	1.714781	0.10	0.917	-3.181602	3.540214
inc2w2	.5322943	1.648367	0.32	0.747	-2.698446	3.763035
inc3w2	-.4148838	1.696991	-0.24	0.807	-3.740924	2.911157
inc4w2	-.3610821	2.088477	-0.17	0.863	-4.454421	3.732257
radhlw2	.0084415	.0066869	1.26	0.207	-.0046645	.0215475
havmil	-.0012719	.0033206	-0.38	0.702	-.0077802	.0052364
avgcumdosew2	.131101	.1238204	1.06	0.290	-.1115826	.3737846
bf1	-.0011966	.0090476	-0.13	0.895	-.0189295	.0165364
bf4	-.1626538	.0410542	-3.96	0.000	-.2431185	-.0821891
bf6	-.0040259	.0075131	-0.54	0.592	-.0187513	.0106995
bf7	-.07395	.0811067	-0.91	0.362	-.2329163	.0850162
bf14	-.000028	.0000759	-0.37	0.712	-.0001769	.0001208
bf15	0	(omitted)				
bf40	.0142117	.0784184	0.18	0.856	-.1394855	.1679089
deaw2	.0365782	.2150994	0.17	0.865	-.3850089	.4581654
dvcew2	-.8025004	1.585115	-0.51	0.613	-3.909268	2.304268
sepaw2	-.5574826	2.582905	-0.22	0.829	-5.619883	4.504918
accdw2	-.5477504	.6503834	-0.84	0.400	-1.822478	.7269777
movew2	.1966685	.5120534	0.38	0.701	-.8069378	1.200275
illw2	.5493357	.2439985	2.25	0.024	.0711074	1.027564
shfamw2	.0017721	.0066016	0.27	0.788	-.0111667	.0147109
shhlw2	.0069859	.006691	1.04	0.296	-.0061281	.0201
shjobw2	-.0075261	.0063225	-1.19	0.234	-.019918	.0048658
shrelaw2	-.0137558	.0073868	-1.86	0.063	-.0282337	.000722
suprtw2	-.0141433	.0055222	-2.56	0.010	-.0249667	-.0033199

suchrw2	.0162332	.0063006	2.58	0.010	.0038842	.0285821
havmilsq	-1.92e-07	2.92e-06	-0.07	0.948	-5.91e-06	5.53e-06
radhlw2	0	(omitted)				
_cons	7.796544	856.9744	0.01	0.993	-1671.842	1687.436

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	59	19	78
-	34	250	284
Total	93	269	362

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	63.44%
Specificity	$\Pr(- \sim D)$	92.94%
Positive predictive value	$\Pr(D +)$	75.64%
Negative predictive value	$\Pr(\sim D -)$	88.03%

False + rate for true ~D	$\Pr(+ \sim D)$	7.06%
False - rate for true D	$\Pr(- D)$	36.56%
False + rate for classified +	$\Pr(\sim D +)$	24.36%
False - rate for classified -	$\Pr(D -)$	11.97%

Correctly classified	85.36%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      362
number of covariate patterns =    362
    Pearson chi2(316) =    350.60
        Prob > chi2 =    0.0877

```

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

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-120.000
D(312):	239.999	LR(45):	172.533
		Prob > LR:	0.000
McFadden's R2:	0.418	McFadden's Adj R2:	0.176
Maximum Likelihood R2:	0.379	Cragg & Uhler's R2:	0.557
McKelvey and Zavoina's R2:	0.643	Efron's R2:	0.461
Variance of y*:	9.209	Variance of error:	3.290
Count R2:	0.854	Adj Count R2:	0.430
AIC:	0.939	AIC*n:	339.999
BIC:	-1598.194	BIC':	92.591

```

911 .
912 . *-----Chunk 7 dose3 moderator => sex life impact-----
913 . title4 "Chunk 7 trimmed male model of dose=>HP2sxlife relationship in Wave 2
> "

```

Chunk 7 trimmed male model of dose=>HP2sxlife relationship in Wave 2

```

914 .
915 .
916 .      forvalues j = 2/2 {
      2.      set more off
      3. di as input  "trimmed HP2sexlife main effects models wave 2 for H1 part 2
> with dose ns"
      4. di as input  "Wave 2 male dose avgcumdosew`j' main effect not signif"
      5.      logit HP2sxlife age bf4 bf40 shjobw`j' shrelaw`j' ///
>      avgcumdosew`j' radhlw`j' if gender==1
      6.      estat class
      7.      estat gof
      8.      fitstat
      9. }
trimmed HP2sexlife main effects models wave 2 for H1 part 2 with dose ns
Wave 2 male dose avgcumdosew2 main effect not signif

```

```

Iteration 0:  log likelihood = -171.28676
Iteration 1:  log likelihood = -117.44151
Iteration 2:  log likelihood = -108.76579
Iteration 3:  log likelihood = -108.4925
Iteration 4:  log likelihood = -108.49198
Iteration 5:  log likelihood = -108.49198

```

Logistic regression	Number of obs	=	339
	LR chi2(7)	=	125.59
	Prob > chi2	=	0.0000
Log likelihood = -108.49198	Pseudo R2	=	0.3666

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0692209	.0165755	4.18	0.000	.0367336	.1017083
bf4	-.1778019	.0383619	-4.63	0.000	-.2529899	-.1026139
bf40	.2569586	.1044384	2.46	0.014	.052263	.4616542
shjobw2	.0128933	.0053503	2.41	0.016	.002407	.0233797
shrelaw2	-.0156464	.0059351	-2.64	0.008	-.0272789	-.0040138
avgcumdosew2	.0651668	.0461706	1.41	0.158	-.025326	.1556596
radhlw2	.0107755	.0056169	1.92	0.055	-.0002334	.0217845
_cons	-4.746559	1.209875	-3.92	0.000	-7.117869	-2.375248

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	35	17	52
-	34	253	287
Total	69	270	339

Classified + if predicted Pr(D) >= .5

True D defined as HP2sxlife != 0

Sensitivity	Pr(+ D)	50.72%
Specificity	Pr(- ~D)	93.70%
Positive predictive value	Pr(D +)	67.31%
Negative predictive value	Pr(~D -)	88.15%

False + rate for true ~D	Pr(+ ~D)	6.30%
False - rate for true D	Pr(- D)	49.28%
False + rate for classified +	Pr(~D +)	32.69%
False - rate for classified -	Pr(D -)	11.85%

Correctly classified	84.96%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      339
number of covariate patterns =    337
Pearson chi2(329) =      258.99
Prob > chi2 =      0.9983

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-171.287	Log-Lik Full Model:	-108.492
D(331):	216.984	LR(7):	125.590
		Prob > LR:	0.000
McFadden's R2:	0.367	McFadden's Adj R2:	0.320
Maximum Likelihood R2:	0.310	Cragg & Uhler's R2:	0.487
McKelvey and Zavoina's R2:	0.539	Efron's R2:	0.374
Variance of y*:	7.131	Variance of error:	3.290
Count R2:	0.850	Adj Count R2:	0.261
AIC:	0.687	AIC*n:	232.984
BIC:	-1711.422	BIC':	-84.808

```

917 .
918 .
919 . title "Chunk 7 trimmed male model of dose and HP2sxlife relationship in Wave
> 2"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****Chunk 7 trimmed male model of dose and HP2sxlife relationship in Wave 2**
> ***
*****
> *
*****
> *
*****
> *
*****
17 Jun 2012    10:08:33    ****
> *
*****
> *
*****
> *

```

```
920 . title4 "h1 pt 2 wave 2 dose=> sex life impact on males"
```

```
h1 pt 2 wave 2 dose=> sex life impact on males
```

```
921 .      forvalues j = 2/2 {
      2. set more off
      3. di as input  "fully trimmed HP2sexlife main effects models wave 2 for H1
> part 2 with dose ns"
      4. di as input  "Wave 2 male dose avgcumdosew`j' main effect not signif"
      5.      logit HP2sxlife age  bf4 bf40  shjobw`j' shrelaw`j' radhlw`j' if
> gender==1
      6.                  estat class
      7.                  estat gof
      8.                  fitstat
      9. }
```

```
fully trimmed HP2sexlife main effects models wave 2 for H1 part 2 with dose ns
Wave 2 male dose avgcumdosew2 main effect not signif
```

```
Iteration 0:  log likelihood = -171.28676
Iteration 1:  log likelihood = -118.10861
Iteration 2:  log likelihood = -109.63863
Iteration 3:  log likelihood = -109.40374
Iteration 4:  log likelihood = -109.4033
Iteration 5:  log likelihood = -109.4033
```

Logistic regression	Number of obs	=	339
	LR chi2(6)	=	123.77
	Prob > chi2	=	0.0000
Log likelihood = -109.4033	Pseudo R2	=	0.3613

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0705974	.0164196	4.30	0.000	.0384155	.1027793
bf4	-.1718905	.0378146	-4.55	0.000	-.2460057	-.0977752
bf40	.2536857	.1036173	2.45	0.014	.0505995	.4567718
shjobw2	.0130156	.0053119	2.45	0.014	.0026045	.0234267
shrelaw2	-.0151881	.005885	-2.58	0.010	-.0267224	-.0036537
radhlw2	.01122	.0055806	2.01	0.044	.0002821	.0221578
_cons	-4.840268	1.202272	-4.03	0.000	-7.196679	-2.483857

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	35	16	51
-	34	254	288
Total	69	270	339

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	50.72%
Specificity	$\Pr(- \sim D)$	94.07%
Positive predictive value	$\Pr(D +)$	68.63%
Negative predictive value	$\Pr(\sim D -)$	88.19%
False + rate for true ~D	$\Pr(+ \sim D)$	5.93%
False - rate for true D	$\Pr(- D)$	49.28%
False + rate for classified +	$\Pr(\sim D +)$	31.37%
False - rate for classified -	$\Pr(D -)$	11.81%
Correctly classified		85.25%

Logistic model for HP2sxlife, goodness-of-fit test

```

      number of observations =      339
number of covariate patterns =      336
      Pearson chi2(329) =      260.66
              Prob > chi2 =      0.9978

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-171.287	Log-Lik Full Model:	-109.403
D(332):	218.807	LR(6):	123.767
		Prob > LR:	0.000
McFadden's R2:	0.361	McFadden's Adj R2:	0.320
Maximum Likelihood R2:	0.306	Cragg & Uhler's R2:	0.481
McKelvey and Zavoina's R2:	0.533	Efron's R2:	0.369
Variance of y*:	7.046	Variance of error:	3.290
Count R2:	0.853	Adj Count R2:	0.275
AIC:	0.687	AIC*n:	232.807
BIC:	-1715.425	BIC':	-88.811

```

922 .
923 . 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)

```

924 . scalar MainEffsxlifeMw2 = "age bf4 bf40 shjobw2 shrelaw2 radhlw2"

```

```

925 . scalar SigDosesxlifeMw2 = "no"

```

```

926 .
927 .
928 . forvalues j = 2/2 {
      2. title "trimmed HP2sxlife main effects models wave `j' for H1 part 2 with
> dose ns"
      3. title2 "Wave `j' dose HPsxlife relationship but avgcumdosew`j': Dose not s
> ignif"
      4. }

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****trimmed HP2sxlife main effects models wave 2 for H1 part 2 with dose ns**
> ***
*****
> *
*****
> *
*****
> *
*****17 Jun 2012 10:08:35 *****
> *
*****
> *
*****
> *

```

```

title2: Wave `j` dose HPsxlife relationship but avgcumdosew2: Dose not signif
Date and time: 17 Jun 2012 10:08:35
Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/hltests/hlpt2
Stata data file: chwide16june2012.dta
> has 2389 variables and 703 observations

Wave `j` dose HPsxlife relationship but avgcumdosew2: Dose not signif

```

```

929 .
930 .
931 . cap gen radhlw2Xd2 = radhlw2*avgcumdosew2

932 .
933 . set more off

934 . des bf4

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```

935 . forvalues j = 2/2 {
      2.          sw, pr(.1):logistic HP2sxlife age bf4 ///
>          avgcumdosew`j' ageXd2 b4Xd2 radhlw2Xd2 shrelaw2Xd2 if gende
> r==1, coef
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.9312 >= 0.1000 removing avgcumdosew2
p = 0.5672 >= 0.1000 removing shrelaw2Xd2
p = 0.2145 >= 0.1000 removing b4Xd2
p = 0.3019 >= 0.1000 removing radhlw2Xd2
p = 0.1093 >= 0.1000 removing ageXd2

```

Logistic regression	Number of obs	=	339
	LR chi2(2)	=	105.12
	Prob > chi2	=	0.0000
Log likelihood = -118.72735	Pseudo R2	=	0.3069

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0733348	.015158	4.84	0.000	.0436256	.1030439
bf4	-.2009901	.0322101	-6.24	0.000	-.2641207	-.1378596
_cons	-3.045295	.9455387	-3.22	0.001	-4.898517	-1.192073

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	32	14	46
-	37	256	293
Total	69	270	339

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

Sensitivity	$\Pr(+ D)$	46.38%
Specificity	$\Pr(- \sim D)$	94.81%
Positive predictive value	$\Pr(D +)$	69.57%
Negative predictive value	$\Pr(\sim D -)$	87.37%
False + rate for true ~D	$\Pr(+ \sim D)$	5.19%
False - rate for true D	$\Pr(- D)$	53.62%
False + rate for classified +	$\Pr(\sim D +)$	30.43%
False - rate for classified -	$\Pr(D -)$	12.63%
Correctly classified		84.96%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      339
number of covariate patterns =    221
    Pearson chi2(218) =    214.23
        Prob > chi2 =    0.5595

```

Measures of Fit for **logistic** of HP2sxlife

```
936 .  
937 . scalar sxlifeModMw2 = "none"  
  
938 . *xx male moderators: no main significant dose effect  
939 . *xx no male moderators for sexlife impact  
940 .  
941 .  
942 .  
943 . title4 "H1 pt2 wave 2 female dose=> sexlife impact models"  
  
-----  
H1 pt2 wave 2 female dose=> sexlife impact models  
-----  
  
944 .  
945 . *-----Chunk 7 dose3 moderator => sex life impact-----  
> -  
946 . di as input "chunk 7   female wave=3"  
      chunk 7   female wave=3  
  
947 . title "Chunk 7 trimmed female model:" "dose and HP2sxlife relationship in Wa  
> ve 2"  
  
  
*****  
> *  
*****  
> *  
*****                               ****  
> *  
*****                               ****  
> *  
*****                               ****  
*****           Chunk 7 trimmed female model:           *****  
> *  
*****           dose and HP2sxlife relationship in Wave 2          *****  
> *  
*****                               ****  
> *  
*****                               ****
```

```

> *
*****
17 Jun 2012    10:08:44    ****
> *
*****
> *
*****
> *

```

```

948 . * female models
949 .     forvalues j = 2/2 {
      2.
950 . set more off
      3. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      4. title4 "trimmed HP2sexlife main effects models" "Wave 2 for H1 part 2 wit
> h dose ns"
      5. title4 "Wave 2 dose HP2sexlife relationship" "avgcumdosew`j' Dose not sig
> nif"
      6.     logit HP2sxlife age  radhlw`j' bf4 bf4m    ///
>         shrelaw`j' avgcumdosew`j'  if gender==2
      7.             estat class
      8.             estat gof
      9.             fitstat
     10. }

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
trimmed HP2sexlife main effects models				
Wave 2 dose HP2sexlife relationship				

```

Iteration 0:  log likelihood = -207.62116
Iteration 1:  log likelihood = -146.12472
Iteration 2:  log likelihood =  -140.853
Iteration 3:  log likelihood = -140.77782
Iteration 4:  log likelihood = -140.77773
Iteration 5:  log likelihood = -140.77773

```

Logistic regression

```

Number of obs   =      363
LR chi2(6)      =     133.69
Prob > chi2     =      0.0000
Pseudo R2      =      0.3219

```

Log likelihood = -140.77773

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0769754	.0151437	5.08	0.000	.0472942	.1066565
radhlw2	.0086172	.004779	1.80	0.071	-.0007494	.0179837
bf4	-.5726666	.1897808	-3.02	0.003	-.9446301	-.2007032
bf4m	.3839121	.1738091	2.21	0.027	.0432526	.7245716
shrelaw2	-.0125758	.0051727	-2.43	0.015	-.0227141	-.0024375
avgcumdosew2	.1836146	.10587	1.73	0.083	-.0238868	.3911161
_cons	-6.850254	1.580753	-4.33	0.000	-9.948473	-3.752035

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	52	21	73
-	42	248	290
Total	94	269	363

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	55.32%
Specificity	$\Pr(- \sim D)$	92.19%
Positive predictive value	$\Pr(D +)$	71.23%
Negative predictive value	$\Pr(\sim D -)$	85.52%

False + rate for true ~D	$\Pr(+ \sim D)$	7.81%
False - rate for true D	$\Pr(- D)$	44.68%
False + rate for classified +	$\Pr(\sim D +)$	28.77%
False - rate for classified -	$\Pr(D -)$	14.48%

Correctly classified	82.64%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

```
number of observations =      363
number of covariate patterns =    362
Pearson chi2(355) =      403.58
Prob > chi2 =      0.0383
```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-140.778
D(356):	281.555	LR(6):	133.687
		Prob > LR:	0.000
McFadden's R2:	0.322	McFadden's Adj R2:	0.288
Maximum Likelihood R2:	0.308	Cragg & Uhler's R2:	0.452
McKelvey and Zavoina's R2:	0.478	Efron's R2:	0.375
Variance of y*:	6.297	Variance of error:	3.290
Count R2:	0.826	Adj Count R2:	0.330
AIC:	0.814	AIC*n:	295.555
BIC:	-1816.852	BIC':	-98.320

```
951 . scalar SigDoseSxlifeFw2 = "no"

952 . scalar MainEffsxlifeFw2 = "age bf4 bf4m shrelaw2"

953 . *----- constructing possible moderators
954 .
955 .     foreach var in bf4 bf4m shfamw2 shrelaw2 radhlw2 {
956 .         2.         cap gen `var'Xd2 = `var'*avgcumdosew2
957 .         3.         }

958 . scalar sxlifeModFw2="none"

958 . scalar SigDoseSxlifeFw2 = "none"
```

```

959 .
960 .
961 .
962 . *----- testing female moderators
963 . 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*****
*****
> *
*****
> *
*****
17 Jun 2012    10:08:46    ****
> *
*****
> *
*****
> *

964 . * male models
965 .     forvalues j = 2/2 {
    2. set more off
    3. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
    4. title3 "trimmed HP2sexlife main effects models wave 2 for H1 part 2 with
> dose ns"
    5. title "Wave 2 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
    6.     logit HP2sxlife age radhlw`j' bf4 bf4m    ///
>     shrelaw`j' avgcumdosew`j' radhlw`j'Xd2 ///
>     bf4Xd2 shrelaw2Xd2 if gender==2
    7.         estat class
    8.         estat gof
    9.         fitstat
    10. }

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```

title3 : trimmed HP2sexlife main effects models wave 2 for H1 part 2 with dose
> ns
17 Jun 2012
10:08:46
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests
> /h1pt2
Data file chwide16june2012.dta currently has 2391 variables and 703 obs
> ervations

```

```

*****
> *
*****
> *
*****
*****
> *
*****Wave 2 dose HP2sexlife relationship but avgcumdosew2: Dose not signif****
> *
*****
> *
*****
> *
*****
17 Jun 2012 10:08:46 *****
> *
*****
> *
*****
> *

```

Iteration 0: log likelihood = **-207.62116**
 Iteration 1: log likelihood = **-144.70934**
 Iteration 2: log likelihood = **-139.49886**
 Iteration 3: log likelihood = **-139.40604**
 Iteration 4: log likelihood = **-139.40547**
 Iteration 5: log likelihood = **-139.40547**

Logistic regression

Number of obs = **363**
 LR chi2(9) = **136.43**
 Prob > chi2 = **0.0000**
 Pseudo R2 = **0.3286**

Log likelihood = **-139.40547**

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0769717	.0151574	5.08	0.000	.0472638	.1066797
radhlw2	.0057223	.0059638	0.96	0.337	-.0059666	.0174112
bf4	-.5293431	.1942546	-2.72	0.006	-.9100751	-.148611
bf4m	.4034483	.177566	2.27	0.023	.0554253	.7514713
shrelaw2	-.0078072	.0074873	-1.04	0.297	-.022482	.0068677
avgcumdosew2	.6934064	.5417467	1.28	0.201	-.3683976	1.755211
radhlw2Xd2	.0041899	.0048672	0.86	0.389	-.0053497	.0137295
bf4Xd2	-.0848776	.0712662	-1.19	0.234	-.2245568	.0548016
shrelaw2Xd2	-.0065332	.0070873	-0.92	0.357	-.020424	.0073577
_cons	-7.400257	1.693844	-4.37	0.000	-10.72013	-4.080384

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	52	21	73
-	42	248	290
Total	94	269	363

Classified + if predicted Pr(D) >= .5

True D defined as HP2sxlife != 0

Sensitivity	Pr(+ D)	55.32%
Specificity	Pr(- ~D)	92.19%
Positive predictive value	Pr(D +)	71.23%
Negative predictive value	Pr(~D -)	85.52%

False + rate for true ~D	Pr(+ ~D)	7.81%
False - rate for true D	Pr(- D)	44.68%
False + rate for classified +	Pr(~D +)	28.77%
False - rate for classified -	Pr(D -)	14.48%

Correctly classified	82.64%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	363
number of covariate patterns =	362
Pearson chi2(352) =	396.16
Prob > chi2 =	0.0521

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-139.405
D(353):	278.811	LR(9):	136.431
		Prob > LR:	0.000
Mcfadden's R2:	0.329	Mcfadden's Adj R2:	0.280
Maximum Likelihood R2:	0.313	Cragg & Uhler's R2:	0.460
McKelvey and Zavoina's R2:	0.511	Efron's R2:	0.381
Variance of y*:	6.728	Variance of error:	3.290
Count R2:	0.826	Adj Count R2:	0.330
AIC:	0.823	AIC*n:	298.811
BIC:	-1801.913	BIC':	-83.382

966 . // trimming further

967 . title "fully female moderator model of dose & HP2sxlife relationship in wv 3
> "

```
*****
> *
*****
> *
*****
> *
*****fully female moderator model of dose & HP2sxlife relationship in wv 3****
> *
*****
> *
*****
> *
*****
17 Jun 2012    10:08:47    ****
> *
*****
> *
*****
```

```
> *
```

```
968 .
969 .
970 . * female models
971 . set more off

972 .      forvalues j = 2/2 {
      2. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      3. title3 "trimmed HP2sexlife main effects models wave 2 for H1 part 2 with
> dose ns"
      4. title "Wave 2 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      5.      logit HP2sxlife age radhlw`j' bf4 bf4m    ///
>      shrelaw2 avgcumdosew`j'    ///
>      shrelaw2Xd2 if gender==2
      6.      estat class
      7.      estat gof
      8.      fitstat
      9. }
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```
title3 : trimmed HP2sexlife main effects models wave 2 for H1 part 2 with dose
> ns
17 Jun 2012
10:08:47
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests
> /h1pt2
Data file chwide16june2012.dta currently has 2391 variables and 703 obs
> ervations
```

```

*****
> *
*****
> *
*****
> *
*****Wave 2 dose HP2sexlife relationship but avgcumdosew2: Dose not signif****
> *
*****
> *
*****
> *
*****
17 Jun 2012    10:08:47    ****
> *
*****
> *
*****
> *

```

```

Iteration 0:  log likelihood = -207.62116
Iteration 1:  log likelihood = -146.11433
Iteration 2:  log likelihood = -140.84565
Iteration 3:  log likelihood = -140.77068
Iteration 4:  log likelihood = -140.7706
Iteration 5:  log likelihood = -140.7706

```

```

Logistic regression              Number of obs   =       363
                                LR chi2(7)       =       133.70
                                Prob > chi2       =       0.0000
Log likelihood = -140.7706      Pseudo R2      =       0.3220

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0768976	.0151557	5.07	0.000	.047193	.1066023
radhlw2	.0086944	.0048244	1.80	0.072	-.0007613	.01815
bf4	-.573012	.189755	-3.02	0.003	-.944925	-.201099
bf4m	.3843277	.1738016	2.21	0.027	.0436827	.7249726
shrelaw2	-.0121114	.0064605	-1.87	0.061	-.0247738	.0005511
avgcumdosew2	.1989447	.1682782	1.18	0.237	-.1308745	.5287638
shrelaw2Xd2	-.0004728	.0039577	-0.12	0.905	-.0082297	.0072841
_cons	-6.867737	1.587757	-4.33	0.000	-9.979683	-3.755791

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	52	22	74
-	42	247	289
Total	94	269	363

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

Sensitivity	$\Pr(+ D)$	55.32%
Specificity	$\Pr(- \sim D)$	91.82%
Positive predictive value	$\Pr(D +)$	70.27%
Negative predictive value	$\Pr(\sim D -)$	85.47%
False + rate for true ~D	$\Pr(+ \sim D)$	8.18%
False - rate for true D	$\Pr(- D)$	44.68%
False + rate for classified +	$\Pr(\sim D +)$	29.73%
False - rate for classified -	$\Pr(D -)$	14.53%
Correctly classified		82.37%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations = **363**
 number of covariate patterns = **362**
 Pearson chi2(**354**) = **403.17**
 Prob > chi2 = **0.0365**

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-140.771
D(355):	281.541	LR(7):	133.701
		Prob > LR:	0.000
McFadden's R2:	0.322	McFadden's Adj R2:	0.283
Maximum Likelihood R2:	0.308	Cragg & Uhler's R2:	0.452
McKelvey and Zavoina's R2:	0.478	Efron's R2:	0.375
Variance of y*:	6.298	Variance of error:	3.290
Count R2:	0.824	Adj Count R2:	0.319
AIC:	0.820	AIC*n:	297.541
BIC:	-1810.972	BIC':	-92.440

```

973 . * female models
974 .       forvalues j = 2/2 {
      2. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      3. title3 "trimmed HP2sexlife main effects models wave 2 for H1 part 2 with
> dose ns"
      4. title "Wave 2 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      5.       logit HP2sxlife age  radhlw`j' bf4 bf4m   ///
>       shrelaw2 shfamw`j'   ///
>       if gender==2
      6.               estat class
      7.               estat gof
      8.               fitstat
      9. }

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```

title3 : trimmed HP2sexlife main effects models wave 2 for H1 part 2 with dose
> ns
17 Jun 2012
10:08:49
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests
> /h1pt2
Data file chwide16june2012.dta currently has 2391 variables and 703 obs
> ervations

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****Wave 2 dose HP2sexlife relationship but avgcumdosew2: Dose not signif****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *

```

```

Iteration 0: log likelihood = -206.26609
Iteration 1: log likelihood = -147.80582
Iteration 2: log likelihood = -142.56802
Iteration 3: log likelihood = -142.50325
Iteration 4: log likelihood = -142.50319
Iteration 5: log likelihood = -142.50319

```

```

Logistic regression
Log likelihood = -142.50319

Number of obs   =      362
LR chi2(6)      =     127.53
Prob > chi2     =      0.0000
Pseudo R2      =      0.3091

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0773867	.0151879	5.10	0.000	.0476189	.1071545
radhlw2	.0092803	.0047101	1.97	0.049	.0000487	.0185119
bf4	-.5791652	.1890895	-3.06	0.002	-.9497739	-.2085566
bf4m	.3860275	.1731752	2.23	0.026	.0466104	.7254445
shrelaw2	-.0111587	.0058224	-1.92	0.055	-.0225703	.000253
shfamw2	-.0012219	.005072	-0.24	0.810	-.0111628	.008719
_cons	-6.703691	1.604696	-4.18	0.000	-9.848837	-3.558545

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	49	23	72
-	44	246	290
Total	93	269	362

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	52.69%
Specificity	$\Pr(- \sim D)$	91.45%
Positive predictive value	$\Pr(D +)$	68.06%
Negative predictive value	$\Pr(\sim D -)$	84.83%
False + rate for true ~D	$\Pr(+ \sim D)$	8.55%
False - rate for true D	$\Pr(- D)$	47.31%
False + rate for classified +	$\Pr(\sim D +)$	31.94%
False - rate for classified -	$\Pr(D -)$	15.17%
Correctly classified		81.49%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      362
number of covariate patterns =    357
    Pearson chi2(350) =    401.39
        Prob > chi2 =      0.0301

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-142.503
D(355):	285.006	LR(6):	127.526
		Prob > LR:	0.000
McFadden's R2:	0.309	McFadden's Adj R2:	0.275
Maximum Likelihood R2:	0.297	Cragg & Uhler's R2:	0.437
McKelvey and Zavoina's R2:	0.465	Efron's R2:	0.360
Variance of y*:	6.146	Variance of error:	3.290
Count R2:	0.815	Adj Count R2:	0.280
AIC:	0.826	AIC*n:	299.006
BIC:	-1806.527	BIC':	-92.176

```

975 .
976 . scalar MainEffsxlifeFw2 = "age radhlw2 bf4 bf4m"

977 . scalar SigDoseSxlifeFw2="no"

978 . scalar SxLifeModFw2 = "no"

979 . * xx female main effects model: no sign dose main effect
980 . * xx 6 signif main effects
981 . * xx no moderator effects significant
982 .
983 . title4 "h1 pt 2 wave 2 dose-> sexlife sexlife mediator impact models"

```

```
h1 pt 2 wave 2 dose-> sexlife sexlife mediator impact models
```

```

984 .
985 . di as input "testing possible sex life mediator effects for males"
    testing possible sex life mediator effects for males

986 .
987 . * age is a mediating effect for males for Dose=> sex life for men
988 . 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)

```
989 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1330.6004
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853

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

	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
990 . 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 : ML 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.)
```

```
991 .
```

```

992 .
993 . des illw2

```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```

994 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-303.59609**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988

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

	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew2	.0085423	.0128556		0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406		7.96	0.000	.2066336	.3416382

```

995 . glm HP2sxlife illw2 if gender==1, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **327.4086**
 Iteration 2: deviance = **327.3702**
 Iteration 3: deviance = **327.3699**
 Iteration 4: deviance = **327.3699**
 Iteration 5: deviance = **327.3699**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 327.36992	(1/df) Deviance	=	.9685501
Pearson = 335.9738293	(1/df) Pearson	=	.9940054

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1642.814

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.4754044	.1211711	3.92	0.000	.2379134	.7128953
_cons	-.9963884	.0886054	-11.25	0.000	-1.170052	-.822725

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

996 .
 997 . des radhlw2

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		how much believed personal health is affected by radiation in 1996

998 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1693.4076

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
Deviance = 421801.4584	Scale parameter	=	1247.933
Pearson = 421801.4584	(1/df) Deviance	=	1247.933
	(1/df) Pearson	=	1247.933

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

Log likelihood = -1693.407647	AIC	=	9.972986
	BIC	=	419831.3

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

```
999 . glm HP2sxlife radhlw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 299.0301
Iteration 2:  deviance = 296.5897
Iteration 3:  deviance = 296.5625
Iteration 4:  deviance = 296.5625
Iteration 5:  deviance = 296.5625
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  MQL Fisher scoring      Residual df    =       338
                    (IRLS EIM)              Scale parameter =         1
Deviance          = 296.5625078              (1/df) Deviance = .8774039
Pearson           = 336.752315              (1/df) Pearson  = .9963086
```

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

```
BIC = -1673.621
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0156386	.0022528	6.94	0.000	.0112232	.020054
_cons	-1.687381	.1543913	-10.93	0.000	-1.989983	-1.38478

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

```
1000 .
1001 .
1002 . des bf4
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
1003 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

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

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

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

	<u>AIC</u>	=	6.053662
Log likelihood = -1027.122509	<u>BIC</u>	=	6404.476

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

```
1004 . 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.)

```
1005 .
1006 . des bf4m
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1007 . glm bf4m avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

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

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

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

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

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

```
1008 . 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.)

```
1009 .
1010 . des shrelaw2
```

variable name	storage type	display format	value label	variable label
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996

```
1011 . glm shrelaw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1686.1612
```

```
Generalized linear models                               No. of obs      =       339
Optimization      : ML                                Residual df     =       337
                                                         Scale parameter =    1231.384
Deviance          =    414976.438                      (1/df) Deviance =    1231.384
Pearson           =    414976.438                      (1/df) Pearson  =    1231.384
```

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

```
Log likelihood    =   -1686.16125                      AIC              =    9.959653
                                                         BIC              =   413013.1
```

shrelaw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.6230115	.7612097	0.82	0.413	-.868932	2.114955
_cons	26.21356	2.042278	12.84	0.000	22.21077	30.21635

```
1012 . glm HP2sxlife shrelaw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance =    340.048
Iteration 2: deviance =    339.8281
Iteration 3: deviance =    339.828
Iteration 4: deviance =    339.828
```

```
Generalized linear models                               No. of obs      =       339
Optimization      : MQL Fisher scoring                  Residual df     =       337
                   (IRLS EIM)                           Scale parameter =         1
Deviance          =    339.8280445                      (1/df) Deviance =    1.008392
Pearson           =    339.1270644                      (1/df) Pearson  =    1.006312
```

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

```
BIC              =   -1623.534
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw2	.0035605	.0021514	1.65	0.098	-.0006562	.0077772
_cons	-.9307902	.1003805	-9.27	0.000	-1.127532	-.734048

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

```
1013 .
1014 . des shfamw2
```

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

```
1015 . glm shfamw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1704.8947**

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1375.284
Deviance = 463470.769	(1/df) Deviance	=	1375.284
Pearson = 463470.769	(1/df) Pearson	=	1375.284

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

	<u>AIC</u>	=	10.07017
Log likelihood = -1704.894657	<u>BIC</u>	=	461507.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.7484378	.8043765	-0.93	0.352	-2.324987	.8281112
_cons	34.76184	2.15791	16.11	0.000	30.53241	38.99127

```
1016 . glm HP2sxlife shfamw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 338.2157
Iteration 2:  deviance = 338.0066
Iteration 3:  deviance = 338.0065
Iteration 4:  deviance = 338.0065
```

```
Generalized linear models                                No. of obs      =       339
Optimization      : ML Fisher scoring                  Residual df     =       337
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 338.0064771                        (1/df) Deviance = 1.002987
Pearson           = 339.3157137                        (1/df) Pearson  = 1.006872
```

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

```
BIC = -1625.356
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	.0027669	.0020626	1.34	0.180	-.0012757	.0068096
_cons	-.9380005	.1081399	-8.67	0.000	-1.149951	-.7260503

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

```
1017 .
1018 . scalar sxlifeMedMw2 = "age"

1019 .
1020 . title4 "female impact models mediator search"
```

```
female impact models mediator search
```

```
1021 .
```

```

1022 . * age is a mediating effect for females for Dose=> sex life for women
1023 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
		Scale parameter	=	136.9184
Deviance	= 49427.52828	(1/df) Deviance	=	136.9184
Pearson	= 49427.52828	(1/df) Pearson	=	136.9184
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271		<u>BIC</u>	=	47299.65

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

```

1024 . 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.)

```

1025 .
1026 . * illness is a mediating effect for females = > sex life for men
1027 . des illw2

```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```

1028 . glm illw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

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

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

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

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

```
1029 . glm HP2sxlife illw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 388.6886
Iteration 2:  deviance = 388.2329
Iteration 3:  deviance = 388.2328
Iteration 4:  deviance = 388.2328
```

```
Generalized linear models                      No. of obs      =       363
Optimization      :  MQL Fisher scoring        Residual df     =       361
                  (IRLS EIM)                  Scale parameter =         1
Deviance          = 388.2327887                (1/df) Deviance = 1.075437
Pearson           = 359.7775997                (1/df) Pearson  = .9966138
```

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

```
BIC = -1739.647
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.4442672	.0949037	4.68	0.000	.2582594	.630275
_cons	-.8535276	.0872416	-9.78	0.000	-1.024518	-.6825372

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

```
1030 .
1031 . *----- this may be important -----
1032 . * radhlw2 can be a mediating factor for females in wave 2 for sxlife
1033 . des radhlw2
```

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		how much believed personal health is affected by radiation in 1996

```
1034 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1791.2233
```

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

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

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

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

```
1035 . glm HP2sxlife radhlw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 390.2214
Iteration 2: deviance = 389.9357
Iteration 3: deviance = 389.9356
Iteration 4: deviance = 389.9356
```

Generalized linear models		No. of obs	=	363
Optimization	: MQL Fisher scoring	Residual df	=	361
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 389.935535	(1/df) Deviance	=	1.080154
Pearson	= 370.7850434	(1/df) Pearson	=	1.027105

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

	BIC	=	-1737.944
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0108547	.0023275	4.66	0.000	.0062929	.0154166
_cons	-1.340315	.1718732	-7.80	0.000	-1.67718	-1.003449

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

```

1036 . *-----
1037 . > --
1038 . des bf4    // soma recentered

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```

1039 . * bf4 is a meditating effect for females for Dose=> sex life for women
1040 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

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

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

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

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

```
1041 . glm HP2sxlife bf4 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 344.0399
Iteration 2: deviance = 342.6827
Iteration 3: deviance = 342.6686
Iteration 4: deviance = 342.6686
Iteration 5: deviance = 342.6686
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : MQL Fisher scoring                Residual df     =       361
                   (IRLS EIM)                          Scale parameter =        1
Deviance          = 342.6686152                        (1/df) Deviance =  .9492205
Pearson           = 336.3540555                        (1/df) Pearson  =  .9317287
```

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

```
1042 .
1043 . des bf4m // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1044 . * bf4m is a possible mediating effect for female sex life
```

```
1045 . glm bf4m avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

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

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

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

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

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.599311	.2139789	-2.80	0.005	-1.018702	-.1799202
_cons	18.83424	.3518214	53.53	0.000	18.14469	19.5238

```
1046 . 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.)

```
1047 .
1048 . des shfamw2
```

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

```
1049 . glm shfamw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1804.1821**

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	360
	Scale parameter	=	1255.79
Deviance = 452084.3956	(1/df) Deviance	=	1255.79
Pearson = 452084.3956	(1/df) Pearson	=	1255.79

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

	<u>AIC</u>	=	9.978907
Log likelihood = -1804.182119	<u>BIC</u>	=	449963.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.6648412	1.349346	0.49	0.622	-1.979828	3.30951
_cons	33.6876	2.218839	15.18	0.000	29.33876	38.03645

```
1050 . glm HP2sxlife shfamw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 411.7925
Iteration 2:  deviance = 411.1829
Iteration 3:  deviance = 411.1826
Iteration 4:  deviance = 411.1826
```

```
Generalized linear models                               No. of obs      =       362
Optimization      :  MQL Fisher scoring                 Residual df     =       360
                   (IRLS EIM)                           Scale parameter =         1
Deviance          = 411.1826472                         (1/df) Deviance =  1.142174
Pearson           = 361.8999919                         (1/df) Pearson  =  1.005278
```

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

```
BIC = -1709.809
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	-.0023803	.0021918	-1.09	0.277	-.0066761	.0019156
_cons	-.5736929	.1047839	-5.48	0.000	-.7790656	-.3683202

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

```
1051 .
1052 . des shrelaw2
```

variable name	storage type	display format	value label	variable label
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996

```
1053 . glm shrelaw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1767.2727
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	996.9369
Deviance = 359894.211	(1/df) Deviance	=	996.9369
Pearson = 359894.211	(1/df) Pearson	=	996.9369

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

	<u>AIC</u>	=	9.748059
Log likelihood = -1767.272695	<u>BIC</u>	=	357766.3

shrelaw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.945314	1.20186	1.62	0.106	-.4102891	4.300917
_cons	22.64351	1.976084	11.46	0.000	18.77046	26.51657

```
1054 . glm HP2sxlife shrelaw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 415.0412
Iteration 2: deviance = 414.406
Iteration 3: deviance = 414.4058
Iteration 4: deviance = 414.4058
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 414.4057989	(1/df) Deviance	=	1.147939
Pearson = 362.9721983	(1/df) Pearson	=	1.005463

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

	BIC	=	-1713.474
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw2	-.0020918	.0024591	-0.85	0.395	-.0069114	.0027279
_cons	-.5970179	.0953785	-6.26	0.000	-.7839564	-.4100794

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

1055 .

1056 . glm aborw2 avgcumdosew2 if gender==2, fam(pois) link(log)

Iteration 0: log likelihood = **-293.85682**
Iteration 1: log likelihood = **-282.01816**
Iteration 2: log likelihood = **-281.9464**
Iteration 3: log likelihood = **-281.94638**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1
Deviance = 391.5624729	(1/df) Deviance	=	1.084661
Pearson = 595.1604651	(1/df) Pearson	=	1.648644

Variance function: **V(u) = u** [Poisson]
Link function : **g(u) = ln(u)** [Log]

	<u>AIC</u>	=	1.564443
Log likelihood = -281.9463797	<u>BIC</u>	=	-1736.317

aborw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0526825	.0821516	-0.64	0.521	-.2136968	.1083317
_cons	-1.095949	.1143769	-9.58	0.000	-1.320124	-.8717744

```
1057 . glm HP2sxlife aborw2 if gender==2, fam(bin) link(probit) irls scale(dev)
```

```
Iteration 1:  deviance = 412.7431
Iteration 2:  deviance = 412.0513
Iteration 3:  deviance = 412.0507
Iteration 4:  deviance = 412.0507
```

```
Generalized linear models          No. of obs      =       363
Optimization      :  MQL Fisher scoring      Residual df    =       361
                    (IRLS EIM)              Scale parameter =         1
Deviance          = 412.0507362             (1/df) Deviance = 1.141415
Pearson           = 361.2552584             (1/df) Pearson  = 1.000707
```

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

```
BIC                                     = -1715.829
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
aborw2	-.1967113	.1199217	-1.64	0.101	-.4317535	.0383309
_cons	-.5909716	.0824147	-7.17	0.000	-.7525014	-.4294418

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

```
1058 .
1059 . title4 "h1 pt2 wave 2 sex life impact summary matrix construction"
```

```
h1 pt2 wave 2 sex life impact summary matrix construction
```

```
1060 .
1061 . *xx summary of mediating effects: age and illness mediate sex life for men
1062 . * age illness radhlw2 bf4 bf4m (soma) medi
> ate sex life for women
```

```

1063 .
1064 . scalar sxlifeMedMw2 = "age illw2"

1065 . scalar sxlifeMedFw2 = "age illw2 radhlw2 bf4 bf4m"

1066 . *--- summary matrix contstruction
1067 .
1068 .   matrix define   sxlifeMw2 = J(1,8, 0)

1069 .           matrix define   sxlifeFw2 = J(1,8, 0)

1070 . matrix colnames   sxlifeMw2=  hypnum ptnum wave gender medsig numMA sig numMed
    > sig numMed

1071 .           matrix colnames   sxlifeFw2=  hypnum ptnum wave gender medsig numMA sig
    > g numModsig numMed

1072 .   matrix define   sxlifeMw2= (1, 2, 3, 1, 0, 6, 0, 1 )

1073 .           matrix define   sxlifeFw2= (1, 2, 3, 2, 0, 4, 0, 5)

1074 .           matrix rowname   sxlifeMw2 =   sxlifeMw2

1075 .           matrix rowname   sxlifeFw2 =   sxlifeFw2

1076 .           matlist   sxlifeMw2

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	sxlifeMw2	1	2	3	1	0	
> 6	0	1					

```

1077 .           matlist   sxlifeFw2

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	sxlifeFw2	1	2	3	2	0	
> 4	0	5					

```

1078 .      matrix define H1pt2w2 = ( wkMw2 \ wkFw2 \ hmcMw2 \ hmcFw2 \ sp
> Mw2 \ spFw2 \ prbfamMw2 \ prbfamFw2 \ sxlifeMw2 \ sxlifeFw2 )

```

```

1079 .

```

```

1080 .      matlist H1pt2w2

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	2	1	0	
> 2	0	2					
	r1	1	2	2	2	0	
> 1	0	2					
	r1	1	2	3	1	0	
> 1	0	1					
	r1	1	2	3	2	1	
> 1	0	2					
	spMw2	1	2	3	1	0	
> 4	0	1					
	spFw2	1	2	3	2	1	
> 5	0	3					
	prbfamMw2	1	2	3	1	0	
> 3	0	1					
	prbfamFw2	1	2	3	2	0	
> 3	0	2					
	sxlifeMw2	1	2	3	1	0	
> 6	0	1					
	sxlifeFw2	1	2	3	2	0	
> 4	0	5					

```

1081 .      matrix colnames H1pt2w2 = hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

```

```

1082 .      matrix rownames H1pt2w2 = wkMw2 wkFw2 hmcMw2 hmcFw2 spMw2 spFw2 p
> rbfhmMw2 prbfhmFw2

```

```
1083 .      matlist H1pt2w2
```

		hypnum	ptnum	wave	gender	medsig	numMasi
> g	numModsig	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2	0	2					
	wkFw2	1	2	2	2	0	
> 1	0	2					
	hmcrMw2	1	2	3	1	0	
> 1	0	1					
	hmcrFw2	1	2	3	2	1	
> 1	0	2					
	spMw2	1	2	3	1	0	
> 4	0	1					
	spFw2	1	2	3	2	1	
> 5	0	3					
	prbfhmMw2	1	2	3	1	0	
> 3	0	1					
	prbfhmFw2	1	2	3	2	0	
> 3	0	2					
	prbfhmFw2	1	2	3	1	0	
> 6	0	1					
	prbfhmFw2	1	2	3	2	0	
> 4	0	5					

```

1084 .
1085 .
1086 .
1087 .
1088 . *===== Chunk 8      Dose => interests and Hobbies relationship
1089 .
1090 . title " 6. H1 Wave 2 part2  Dose-Interest and Hobbies impact"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
6. H1 Wave 2 part2 Dose-Interest and Hobbies impact
*****
> *
*****
> *
*****

```

```

> *
*****
17 Jun 2012    10:09:32    ****
> *
*****
> *
*****
> *

1091 .
1092 .
1093 . * Chunk 8 ---male models
1094 . forvalues j = 2/2 {
      2. set more off
      3.
1095 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
>    bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1096 .   foreach var in HP2inthob {
      5.       forvalues k=1/2 {
      6. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      7.
1097 . di as input "Full main model for `var' for wave= `j' "
      8. di _skip(4)
      9. di as input  "chunk 8 H1 test:Gender= `k'  model Wave = `j' for `e(depva
> r)' "
     10. di _skip(4)
     11. title "Full Nottingham Part 2 subscale models for male and then females"
     12. di as input "Model for gender==`k' and wave == `j'"
     13. di _skip(2)
     14.       xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
>           marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
> //
>           radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>           deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>           illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
> chrw`j' ///
>           havmilsq radhlw2 if gender==`k', coef  difficult iterate(50
> )
     15.             estat class
     16.             estat gof
     17.             fitstat
     18. }
     19. }
     20. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= 1 model Wave = 2 for HP2sxlife

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

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 3 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: bf15 omitted because of collinearity
note: radhlw2 omitted because of collinearity

Logistic regression	Number of obs	=	240
	LR chi2(35)	=	92.50
	Prob > chi2	=	0.0000
Log likelihood = -55.199011	Pseudo R2	=	0.4559

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0625698	.0339541	1.84	0.065	-.0039791	.1291186
_Ieduc_2	-1.043358	1.579537	-0.66	0.509	-4.139194	2.052478
_Ieduc_3	-1.383026	.8161024	-1.69	0.090	-2.982558	.216505
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.3882601	.890757	-0.44	0.663	-2.134112	1.357591
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-1.033982	5.222537	-0.20	0.843	-11.26997	9.202003
occ2w2	-2.764859	5.282979	-0.52	0.601	-13.11931	7.58959
occ3w2	-1.159373	5.266774	-0.22	0.826	-11.48206	9.163314
occ4w2	-1.475817	5.272908	-0.28	0.780	-11.81053	8.858893
occ5w2	.6777917	5.260041	0.13	0.897	-9.631698	10.98728
occ6w2	0	(omitted)				
occ7w2	-.3442089	5.327123	-0.06	0.948	-10.78518	10.09676
occ8w2	0	(omitted)				
marrw21	13.93224	1621.282	0.01	0.993	-3163.721	3191.586
marrw22	0	(omitted)				
marrw23	11.47436	1621.282	0.01	0.994	-3166.179	3189.128
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inc1w2	-2.09725	5.429773	-0.39	0.699	-12.73941	8.544909
inc2w2	-.9256519	5.257192	-0.18	0.860	-11.22956	9.378255
inc3w2	.0745765	5.245026	0.01	0.989	-10.20548	10.35464
inc4w2	0	(omitted)				
radhlw2	.0364231	.0131057	2.78	0.005	.0107363	.0621099
havmil	.0020332	.0091412	0.22	0.824	-.0158833	.0199497
avgcumdosew2	-.2023055	.3376483	-0.60	0.549	-.8640841	.4594731

bf1	.0108557	.0182727	0.59	0.552	-.0249582	.0466696
bf4	-.290932	.0816796	-3.56	0.000	-.4510211	-.1308428
bf6	.0111353	.0131635	0.85	0.398	-.0146647	.0369353
bf7	.0337038	.1171208	0.29	0.774	-.1958487	.2632562
bf14	-.000219	.0001127	-1.94	0.052	-.0004398	1.92e-06
bf15	0	(omitted)				
bf40	.490857	.2032201	2.42	0.016	.0925529	.889161
deaw2	.006222	.5178905	0.01	0.990	-1.008825	1.021269
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	1.036869	.5663339	1.83	0.067	-.0731249	2.146863
movew2	.7948452	.8450104	0.94	0.347	-.8613447	2.451035
illw2	-.8262786	.5178561	-1.60	0.111	-1.841258	.1887007
shfamw2	-.003778	.0101348	-0.37	0.709	-.0236419	.0160858
shhlw2	-.0014472	.0125099	-0.12	0.908	-.0259662	.0230717
shjobw2	.0044446	.012101	0.37	0.713	-.0192728	.0281621
shrelaw2	-.0158848	.0098629	-1.61	0.107	-.0352157	.0034461
suprtw2	-.0048211	.0089741	-0.54	0.591	-.0224099	.0127678
suchrw2	.016543	.008867	1.87	0.062	-.0008361	.033922
havmilsq	-2.84e-06	.0000159	-0.18	0.858	-.000034	.0000283
radhlw2	0	(omitted)				
_cons	-16.47971	1621.283	-0.01	0.992	-3194.136	3161.177

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	20	6	26
-	16	198	214
Total	36	204	240

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	55.56%
Specificity	$\Pr(- \sim D)$	97.06%
Positive predictive value	$\Pr(D +)$	76.92%
Negative predictive value	$\Pr(\sim D -)$	92.52%
False + rate for true ~D	$\Pr(+ \sim D)$	2.94%
False - rate for true D	$\Pr(- D)$	44.44%
False + rate for classified +	$\Pr(\sim D +)$	23.08%
False - rate for classified -	$\Pr(D -)$	7.48%
Correctly classified		90.83%

Logistic model for HP2inthob, goodness-of-fit test

```
      number of observations =      240
number of covariate patterns =      240
      Pearson chi2(204) =      545.84
      Prob > chi2 =      0.0000
```

Measures of Fit for logistic of HP2inthob

Log-Lik Intercept Only:	-101.450	Log-Lik Full Model:	-55.199
D(190):	110.398	LR(35):	92.502
		Prob > LR:	0.000
McFadden's R2:	0.456	McFadden's Adj R2:	-0.037
Maximum Likelihood R2:	0.320	Cragg & Uhler's R2:	0.561
McKelvey and Zavoina's R2:	0.776	Efron's R2:	0.482
Variance of y*:	14.694	Variance of error:	3.290
Count R2:	0.908	Adj Count R2:	0.389
AIC:	0.877	AIC*n:	210.398
BIC:	-930.923	BIC':	99.320

Full main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= 2 model Wave = 2 for HP2inthob

```
*****
> *
*****
> *
*****
> *
*****
> *
***** Full Nottingham Part 2 subscale models for male and then females *****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
```

Model for gender==2 and wave == 2

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

note: sepaw2 != 0 predicts failure perfectly

 sepaw2 dropped and 8 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw26 omitted because of collinearity

note: bf15 omitted because of collinearity

note: radhlw2 omitted because of collinearity

Logistic regression

Number of obs = 354

LR chi2(44) = 115.47

Prob > chi2 = 0.0000

Pseudo R2 = 0.3420

Log likelihood = -111.06431

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.079863	.021131	3.78	0.000	.0384469	.121279
_Ieduc_2	-12.93831	1490.754	-0.01	0.993	-2934.762	2908.885
_Ieduc_3	-12.4076	1490.754	-0.01	0.993	-2934.231	2909.416
_Ieduc_4	-11.72169	1490.754	-0.01	0.994	-2933.546	2910.102
_Ieduc_5	-12.09518	1490.754	-0.01	0.994	-2933.919	2909.728
_Ieduc_6	-12.44516	1490.754	-0.01	0.993	-2934.269	2909.378
_Ieduc_7	-12.06531	1490.757	-0.01	0.994	-2933.895	2909.764
_Ieduc_8	0	(omitted)				
occ1w2	-1.681778	1.842381	-0.91	0.361	-5.292779	1.929222
occ2w2	-2.066763	1.905083	-1.08	0.278	-5.800657	1.66713
occ3w2	-.925484	1.867622	-0.50	0.620	-4.585956	2.734988
occ4w2	-1.837685	1.997812	-0.92	0.358	-5.753324	2.077954
occ5w2	-1.808015	2.160492	-0.84	0.403	-6.042501	2.426471
occ6w2	-.7980572	2.0458	-0.39	0.696	-4.807751	3.211637
occ7w2	-.6513668	1.8133	-0.36	0.719	-4.205369	2.902636
occ8w2	-.7497523	2.02704	-0.37	0.711	-4.722678	3.223174
marrw21	1.330155	1.130799	1.18	0.239	-.8861701	3.546479
marrw22	.1433998	1.421047	0.10	0.920	-2.641801	2.9286
marrw23	.3124211	.8029396	0.39	0.697	-1.261312	1.886154
marrw25	.2321157	1.213839	0.19	0.848	-2.146964	2.611196
marrw26	0	(omitted)				
inc1w2	1.002608	1.857433	0.54	0.589	-2.637893	4.643109
inc2w2	1.21648	1.809887	0.67	0.502	-2.330833	4.763793
inc3w2	.8716928	1.845137	0.47	0.637	-2.744709	4.488095
inc4w2	2.25991	2.119136	1.07	0.286	-1.893519	6.41334
radhlw2	.0169047	.0075432	2.24	0.025	.0021202	.0316892
havmil	.0026206	.00401	0.65	0.513	-.0052388	.0104801
avgcumdosew2	.1098391	.1075167	1.02	0.307	-.1008897	.3205679
bf1	-.0101735	.0098443	-1.03	0.301	-.029468	.0091209

bf4	-.160166	.0433489	-3.69	0.000	-.2451282	-.0752038
bf6	-.0029228	.0086097	-0.34	0.734	-.0197974	.0139519
bf7	-.0201783	.0882604	-0.23	0.819	-.1931656	.152809
bf14	-.0000789	.0000837	-0.94	0.346	-.000243	.0000853
bf15	0	(omitted)				
bf40	-.0387073	.0922777	-0.42	0.675	-.2195682	.1421537
deaw2	.1202612	.2113024	0.57	0.569	-.2938838	.5344063
dvcew2	.0143372	1.477099	0.01	0.992	-2.880724	2.909399
sepaw2	0	(omitted)				
accdw2	.4772298	.6036102	0.79	0.429	-.7058243	1.660284
movew2	-.5141092	.7928535	-0.65	0.517	-2.068073	1.039855
illw2	.1586699	.2249295	0.71	0.481	-.2821838	.5995235
shfamw2	-.0005225	.0071722	-0.07	0.942	-.0145799	.0135348
shhlw2	.0069143	.0072142	0.96	0.338	-.0072252	.0210539
shjobw2	-.0096031	.0066833	-1.44	0.151	-.0227021	.003496
shrelaw2	-.011349	.0077316	-1.47	0.142	-.0265027	.0038047
suprtw2	-.01257	.0057932	-2.17	0.030	-.0239246	-.0012155
suchrw2	.000171	.0063873	0.03	0.979	-.0123478	.0126898
havmilsq	-2.75e-06	5.84e-06	-0.47	0.638	-.0000142	8.69e-06
radhlw2	0	(omitted)				
_cons	8.21905	1490.755	0.01	0.996	-2913.607	2930.045

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	35	12	47
-	30	277	307
Total	65	289	354

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	53.85%
Specificity	$\Pr(- \sim D)$	95.85%
Positive predictive value	$\Pr(D +)$	74.47%
Negative predictive value	$\Pr(\sim D -)$	90.23%

False + rate for true ~D	$\Pr(+ \sim D)$	4.15%
False - rate for true D	$\Pr(- D)$	46.15%
False + rate for classified +	$\Pr(\sim D +)$	25.53%
False - rate for classified -	$\Pr(D -)$	9.77%

Correctly classified	88.14%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

```
      number of observations =      354
number of covariate patterns =      354
      Pearson chi2(309) =      384.69
      Prob > chi2 =      0.0022
```

Measures of Fit for logistic of HP2inthob

Log-Lik Intercept Only:	-168.799	Log-Lik Full Model:	-111.064
D(304):	222.129	LR(44):	115.469
		Prob > LR:	0.000
McFadden's R2:	0.342	McFadden's Adj R2:	0.046
Maximum Likelihood R2:	0.278	Cragg & Uhler's R2:	0.453
McKelvey and Zavoina's R2:	0.619	Efron's R2:	0.372
Variance of y*:	8.629	Variance of error:	3.290
Count R2:	0.881	Adj Count R2:	0.354
AIC:	0.910	AIC*n:	322.129
BIC:	-1562.138	BIC':	142.780

1098 .

1099 . label var radhlw2 "Self-perceived Chernobyl health threat in Wave 2"

1100 .

1101 . title4 "7. Testing H1 Wv2 Moderators of male Dose => Interests and Hobbies I
> mpact"

7. Testing H1 Wv2 Moderators of male Dose => Interests and Hobbies Impact

1102 .

1103 .

1104 . forvalues j = 2/2 {
 2. set more off
 3.

```

1105 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
    >   bf4 bf14  bf40
    4.
1106 . foreach var in HP2inthob {
    5. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 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)'"
    > ar)' "
    10. di _skip(4)
    11. title "Full Nottingham Part 2 subscale models " "males on wave=`j'"
    12. des bf5m shfamw2 radhlw2 bf4m
    13. xi: logistic `var' age radhlw2 bf4 bf14 bf40 ///
    > suchrw2 if gender==1, coef 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
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for

	storage	display	value	
variable name	type	format	label	variable label
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
radhlw2	double	%8.0g		Self-perceived Chornobyl health threat in Wave 2
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
Logistic regression				Number of obs = 333
				LR chi2(6) = 69.19
				Prob > chi2 = 0.0000
Log likelihood = -79.471154				Pseudo R2 = 0.3033

Logistic model for HP2inthob

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

Sensitivity	$\Pr(+ D)$	33.33%
Specificity	$\Pr(- \sim D)$	97.98%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	92.38%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	2.02%
False - rate for true D	$\Pr(- D)$	66.67%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	7.62%
Correctly classified		90.99%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      333
number of covariate patterns =    330
    Pearson chi2(323) =    279.79
        Prob > chi2 =      0.9605
  
```

Measures of Fit for **logistic** of HP2inthob

Log-Lik Intercept Only:	-114.066	Log-Lik Full Model:	-79.471
D(326):	158.942	LR(6):	69.190
		Prob > LR:	0.000
McFadden's R2:	0.303	McFadden's Adj R2:	0.242
Maximum Likelihood R2:	0.188	Cragg & Uhler's R2:	0.378
McKelvey and Zavoina's R2:	0.477	Efron's R2:	0.266
Variance of y*:	6.288	Variance of error:	3.290
Count R2:	0.910	Adj Count R2:	0.167
AIC:	0.519	AIC*n:	172.942
BIC:	-1734.512	BIC':	-34.341

Note: bf4m is necessary for bf5 but if bf4m is in model bf5 is not signif.
 Therefore, bf5 is not deemed significant.

```

1107 .
1108 . cap gen bf4Xd2 = bf4*avgcumdosew2

1109 . cap gen bf40Xd2 = bf40*agecumdosew2

1110 .
1111 . scalar SigdoseMEinthob = "no"

1112 . scalar MainEffMw2 = "radhlw2 bf4 bf40"

1113 .
1114 . title3 "Wave 2 Main effects Dose=> Interests and Hobbies impact identificati
> on"

```

```

title3 : Wave 2 Main effects Dose=> Interests and Hobbies impact identificatio
> n
17 Jun 2012
10:09:37
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/hltests
> /hlpt2
Data file chwide16june2012.dta currently has 2384 variables and 703 obs
> ervations

1115 . forvalues j = 2/2 {
      2. set more off
      3.
1116 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
>    bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1117 . foreach var in HP2inthob {
      5. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 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.

```

```

1118 .
1119 .      xi: logistic `var' age    ///
>          radhlw`j' avgcumdosew`j'  ///
>          shfamw`j'  bf4 ///
>          bf40 bf4Xd2 bf40Xd2 if gender==1, coef  difficult iterate(5
> 0)
11.          estat class
12.          estat gof
13.          fitstat
14. }
15. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiw1 - 85) * bf20

bf40 float %9.0g **bf40 = max(0, icdxcnt - 1.01635E-007)**

Full main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= male model Wave = 2 for HP2inthob

Logistic regression	Number of obs	=	339
	LR chi2(8)	=	68.60
	Prob > chi2	=	0.0000
Log likelihood = -84.646353	Pseudo R2	=	0.2884

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.019434	.0190292	1.02	0.307	-.0178625	.0567305
radhlw2	.0239518	.0073094	3.28	0.001	.0096255	.038278
avgcumdosew2	2.556026	1.455092	1.76	0.079	-.2959014	5.407954
shfamw2	-.0013078	.0052959	-0.25	0.805	-.0116875	.0090719
bf4	.0106918	.0838793	0.13	0.899	-.1537086	.1750922
bf40	.4187179	.1715551	2.44	0.015	.082476	.7549597
bf4Xd2	-.1876111	.108152	-1.73	0.083	-.3995851	.0243629
bf40Xd2	-.2942793	.1683543	-1.75	0.080	-.6242477	.035689
_cons	-5.700963	1.702573	-3.35	0.001	-9.037944	-2.363982

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	14	7	21
-	24	294	318
Total	38	301	339

Classified + if predicted Pr(D) >= .5

True D defined as HP2inthob != 0

Sensitivity	Pr(+ D)	36.84%
Specificity	Pr(- ~D)	97.67%
Positive predictive value	Pr(D +)	66.67%
Negative predictive value	Pr(~D -)	92.45%
False + rate for true ~D	Pr(+ ~D)	2.33%
False - rate for true D	Pr(- D)	63.16%
False + rate for classified +	Pr(~D +)	33.33%
False - rate for classified -	Pr(D -)	7.55%

Correctly classified	90.86%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	339
number of covariate patterns =	334
Pearson chi2(325) =	281.60
Prob > chi2 =	0.9606

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

Log-Lik Intercept Only:	-118.946	Log-Lik Full Model:	-84.646
D(330):	169.293	LR(8):	68.598
		Prob > LR:	0.000
McFadden's R2:	0.288	McFadden's Adj R2:	0.213
Maximum Likelihood R2:	0.183	Cragg & Uhler's R2:	0.363
McKelvey and Zavoina's R2:	0.691	Efron's R2:	0.260
Variance of y*:	10.643	Variance of error:	3.290
Count R2:	0.909	Adj Count R2:	0.184
AIC:	0.552	AIC*n:	187.293
BIC:	-1753.287	BIC':	-21.990

1120 . scalar SigDoseInthbMw2 = "no"

1121 . scalar MainEffInthbMw2 = "age radhlw2 shfamw2"

1122 . scalar InthbModMw2 = "none"

1123 .

1124 . *-----chunk 8 female moderator models

1125 . title4 "trimmed Moderators of female Dose => Interests and Hobbies Impact"

trimmed Moderators of female Dose => Interests and Hobbies Impact

```

1126 .
1127 .
1128 . forvalues j = 2/2 {
      2. set more off
      3.
1129 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1130 . foreach var in HP2inthob {
      5. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 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 females "
      11.
1131 . xi: logistic `var' age ///
      > radhlw`j' avgcumdosew`j' ///
      > bf4 ///
      > if gender==2, coef difficult iterate(50)
      12. estat class
      13. estat gof
      14. fitstat
      15. }
      16. }

```

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

Logistic regression

Number of obs = 363

LR chi2(4) = 85.23

Prob > chi2 = 0.0000

Pseudo R2 = 0.2476

Log likelihood = -129.49784

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0747628	.0160244	4.67	0.000	.0433556	.10617
radhlw2	.0174604	.0053569	3.26	0.001	.0069611	.0279597
avgcumdosew2	.0556287	.0871446	0.64	0.523	-.1151717	.226429
bf4	-.0957645	.0312145	-3.07	0.002	-.1569439	-.0345852
_cons	-5.962105	1.09169	-5.46	0.000	-8.101778	-3.822431

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	27	8	35
-	39	289	328
Total	66	297	363

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	40.91%
Specificity	$\Pr(- \sim D)$	97.31%
Positive predictive value	$\Pr(D +)$	77.14%
Negative predictive value	$\Pr(\sim D -)$	88.11%

False + rate for true ~D	$\Pr(+ \sim D)$	2.69%
False - rate for true D	$\Pr(- D)$	59.09%
False + rate for classified +	$\Pr(\sim D +)$	22.86%
False - rate for classified -	$\Pr(D -)$	11.89%

Correctly classified	87.05%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

number of observations = 363
 number of covariate patterns = 361
 Pearson chi2(356) = 453.01
 Prob > chi2 = 0.0004

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

Log-Lik Intercept Only:	-172.113	Log-Lik Full Model:	-129.498
D(358):	258.996	LR(4):	85.229
		Prob > LR:	0.000
McFadden's R2:	0.248	McFadden's Adj R2:	0.219
Maximum Likelihood R2:	0.209	Cragg & Uhler's R2:	0.342
McKelvey and Zavoina's R2:	0.407	Efron's R2:	0.292
Variance of y*:	5.547	Variance of error:	3.290
Count R2:	0.871	Adj Count R2:	0.288
AIC:	0.741	AIC*n:	268.996
BIC:	-1851.201	BIC':	-61.652

1132 . scalar SigdoseInthbFw2 = "no"

1133 . scalar MainEffInthbFw2 = "age radhlw2 bf4"

1134 .

1135 . title4 "*-----chunk 8 testing female interests and hobbies moderators"

*-----chunk 8 testing female interests and hobbies moderators

1136 .

1137 .

1138 . forvalues j = 2/2 {
 2. set more off
 3.

1139 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
 > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
 4.

1140 . foreach var in HP2inthob {
 5. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
 6. di _skip(4)
 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)
 > ar)' "
 10. di _skip(4)
 11.

```

1141 .      xi: logistic `var' age    ///
>          radhlw`j' avgcumdosew`j' ///
>          bf4 bf4Xd2 ageXd2 radhlw2Xd2 ///
>          if gender==2, coef difficult iterate(50)
12.          estat class
13.          estat gof
14.          fitstat
15. }
16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiw1 - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= male model Wave = 2 for HP2inthob

Logistic regression	Number of obs	=	363
	LR chi2(7)	=	87.82
	Prob > chi2	=	0.0000
Log likelihood = -128.20013	Pseudo R2	=	0.2551

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.069622	.0190503	3.65	0.000	.0322841	.1069599
radhlw2	.0222021	.0063839	3.48	0.001	.00969	.0347143
avgcumdosew2	.0545345	.7778922	0.07	0.944	-1.470106	1.579175
bf4	-.096555	.0395926	-2.44	0.015	-.1741551	-.0189549
bf4Xd2	-.0006382	.0261986	-0.02	0.981	-.0519866	.0507102
ageXd2	.0057178	.0123652	0.46	0.644	-.0185176	.0299531
radhlw2Xd2	-.0041808	.003242	-1.29	0.197	-.0105349	.0021734
_cons	-6.018454	1.285872	-4.68	0.000	-8.538717	-3.498191

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	28	9	37
-	38	288	326
Total	66	297	363

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	42.42%
Specificity	$\Pr(- \sim D)$	96.97%
Positive predictive value	$\Pr(D +)$	75.68%
Negative predictive value	$\Pr(\sim D -)$	88.34%

False + rate for true ~D	$\Pr(+ \sim D)$	3.03%
False - rate for true D	$\Pr(- D)$	57.58%
False + rate for classified +	$\Pr(\sim D +)$	24.32%
False - rate for classified -	$\Pr(D -)$	11.66%

Correctly classified	87.05%
----------------------	---------------

Logistic model for HP2inthob, goodness-of-fit test

```
number of observations =      363
number of covariate patterns =    361
    Pearson chi2(353) =    461.27
        Prob > chi2 =      0.0001
```

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

Log-Lik Intercept Only:	-172.113	Log-Lik Full Model:	-128.200
D(355):	256.400	LR(7):	87.825
		Prob > LR:	0.000
McFadden's R2:	0.255	McFadden's Adj R2:	0.209
Maximum Likelihood R2:	0.215	Cragg & Uhler's R2:	0.351
McKelvey and Zavoina's R2:	0.419	Efron's R2:	0.304
Variance of y*:	5.660	Variance of error:	3.290
Count R2:	0.871	Adj Count R2:	0.288
AIC:	0.750	AIC*n:	272.400
BIC:	-1836.113	BIC':	-46.564

```
1142 . scalar InthbModFw2 = "none"
```

```
1143 .
```

```
1144 . title4 " dose-  interests and hobbies  mediator effect models"
```

```
dose-  interests and hobbies  mediator effect models
```

```
1145 .
```

```
1146 . * age is a mediating effect for males for Dose=> sex life for men
```

```
1147 .
```

```
1148 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1330.6004
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
1149 . 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.)

```
1150 .
```

```
1151 .
1152 . des illw2
```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```
1153 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-303.59609**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988

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

	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew2	.0085423	.0128556		0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406		7.96	0.000	.2066336	.3416382

```
1154 . glm HP2inthob illw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

Iteration 1: deviance = **237.2651**
 Iteration 2: deviance = **236.0196**
 Iteration 3: deviance = **236.0142**
 Iteration 4: deviance = **236.0142**
 Iteration 5: deviance = **236.0142**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 236.0141663	(1/df) Deviance	=	.6982668
Pearson = 338.89241	(1/df) Pearson	=	1.00264

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1734.169

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.2044103	.113873	1.80	0.073	-.0187766	.4275973
_cons	-1.284117	.0852302	-15.07	0.000	-1.451165	-1.117069

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

1155 .
 1156 . des radhlw2

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		Self-perceived Chernobyl health threat in Wave 2

1157 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1693.4076

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933

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

Log likelihood = -1693.407647
 AIC = 9.972986
 BIC = 419831.3

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

```
1158 . glm HP2inthob radhlw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 207.4869
Iteration 2:  deviance = 195.0786
Iteration 3:  deviance = 193.7239
Iteration 4:  deviance = 193.6942
Iteration 5:  deviance = 193.6942
Iteration 6:  deviance = 193.6942
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  ML Fisher scoring                 Residual df     =       338
                   ( IRLS EIM )                       Scale parameter =         1
Deviance          =   193.694234                        (1/df) Deviance =   .5730599
Pearson           =   330.3909814                       (1/df) Pearson  =   .9774881
```

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

```
BIC = -1776.489
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0187765	.0024049	7.81	0.000	.014063	.02349
_cons	-2.360804	.1846104	-12.79	0.000	-2.722634	-1.998974

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

```
1159 .
1160 .
1161 . des shfamw2
```

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

```
1162 . glm shfamw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1704.8947
```

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1375.284
Deviance = 463470.769	(1/df) Deviance	=	1375.284
Pearson = 463470.769	(1/df) Pearson	=	1375.284

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

	<u>AIC</u>	=	10.07017
Log likelihood = -1704.894657	<u>BIC</u>	=	461507.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.7484378	.8043765	-0.93	0.352	-2.324987	.8281112
_cons	34.76184	2.15791	16.11	0.000	30.53241	38.99127

```
1163 . glm HP2inthob shfamw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 236.0134
Iteration 2: deviance = 234.459
Iteration 3: deviance = 234.4495
Iteration 4: deviance = 234.4495
```

Generalized linear models	No. of obs	=	339
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	337
	Scale parameter	=	1
Deviance = 234.4495475	(1/df) Deviance	=	.695696
Pearson = 340.0883436	(1/df) Pearson	=	1.009164

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

	BIC	=	-1728.912
--	-----	---	-----------

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	.0043459	.0019602	2.22	0.027	.0005039	.0081879
_cons	-1.379269	.1084635	-12.72	0.000	-1.591853	-1.166684

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

```
1164 .
1165 . des bf5m
```

variable name	storage type	display format	value label	variable label
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m

```
1166 . glm bf5m avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-2273.2523**

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

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

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

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

```
1167 . glm HP2inthob bf5m if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 238.9021
Iteration 2:  deviance = 238.0124
Iteration 3:  deviance = 238.0098
Iteration 4:  deviance = 238.0098
Iteration 5:  deviance = 238.0098
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  ML Fisher scoring      Residual df      =       338
                    (IRLS EIM)              Scale parameter =         1
Deviance          =  238.0098185          (1/df) Deviance =  .7041711
Pearson           =  339.8073754          (1/df) Pearson  =  1.005347
```

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

```
BIC = -1732.174
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf5m	.0001615	.000378	0.43	0.669	-.0005794	.0009024
_cons	-1.236147	.0878768	-14.07	0.000	-1.408382	-1.063912

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

```
1168 .
```

```
1169 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

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

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

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

```
Log likelihood      = -1027.122509          AIC           =  6.053662
BIC               =  6404.476
```

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

```
1170 . 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.)

```

1171 .
1172 .
1173 . scalar inthobMw2 = "age "

1174 .
1175 . * age is a mediating effect for females for Dose=> sex life for women
1176 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

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

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

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

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

```

1177 . 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 : MQL Fisher scoring	Residual df	=	361
(IRLS EIM)	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]

	BIC	=	-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.)

```
1178 .
1179 . * illw2 is a mediating effect for females for Dose=> sex life for women
1180 . glm illw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

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

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

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

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

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

```
1181 . glm HP2inthob illw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

Iteration 1: deviance = **337.9924**
Iteration 2: deviance = **337.8991**
Iteration 3: deviance = **337.8989**
Iteration 4: deviance = **337.8989**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 337.8988998	(1/df) Deviance	=	.936008
Pearson = 362.1873188	(1/df) Pearson	=	1.003289

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1789.981

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.204938	.0789434	2.60	0.009	.0502118	.3596641
_cons	-1.005064	.0841351	-11.95	0.000	-1.169965	-.8401618

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

1182 .
 1183 . des bf4 // soma recentered

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

1184 . * bf4 is a meditating effect for females for Dose=> sex life for women
 1185 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1109.0983

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

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

Log likelihood = -1109.098281
 AIC = 6.121754
 BIC = 7450.466

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

```
1186 . 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      : ML Fisher scoring                 Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 301.4486672                        (1/df) Deviance =  .8350379
Pearson           = 341.1451194                        (1/df) Pearson  =  .9450003
```

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

```
BIC = -1826.431
```

HP2inthob	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.0993749	.0142594	-6.97	0.000	-.1273229	-.071427
_cons	.0117358	.1447759	0.08	0.935	-.2720197	.2954914

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

```
1187 .
1188 . des bf4m // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1189 . * bf4m is a possible mediating effect for female sex life
```

```
1190 . glm bf4m avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

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

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

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

	AIC	=	6.296561
Log likelihood = -1140.825904	BIC	=	9280.095

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.599311	.2139789	-2.80	0.005	-1.018702	-.1799202
_cons	18.83424	.3518214	53.53	0.000	18.14469	19.5238

```
1191 . 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 : MQL Fisher scoring (IRLS EIM)	Residual df	=	361
	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.)

```
1192 .
1193 . des shfamw2
```

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

```
1194 . glm shfamw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1704.8947**

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1375.284
Deviance = 463470.769	(1/df) Deviance	=	1375.284
Pearson = 463470.769	(1/df) Pearson	=	1375.284

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

	<u>AIC</u>	=	10.07017
Log likelihood = -1704.894657	<u>BIC</u>	=	461507.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.7484378	.8043765	-0.93	0.352	-2.324987	.8281112
_cons	34.76184	2.15791	16.11	0.000	30.53241	38.99127

```
1195 . glm HP2sxlife shfamw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 338.2157
Iteration 2:  deviance = 338.0066
Iteration 3:  deviance = 338.0065
Iteration 4:  deviance = 338.0065
```

```
Generalized linear models                                No. of obs      =       339
Optimization      :  MQL Fisher scoring                  Residual df     =       337
                   (IRLS EIM)                           Scale parameter =         1
Deviance          = 338.0064771                         (1/df) Deviance =  1.002987
Pearson          = 339.3157137                          (1/df) Pearson  =  1.006872
```

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

```
BIC = -1625.356
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	.0027669	.0020626	1.34	0.180	-.0012757	.0068096
_cons	-.9380005	.1081399	-8.67	0.000	-1.149951	-.7260503

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

```
1196 .
1197 . des shrelaw2
```

variable name	storage type	display format	value label	variable label
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996

```
1198 . glm shrelaw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1686.1612
```

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1231.384
Deviance = 414976.438	(1/df) Deviance	=	1231.384
Pearson = 414976.438	(1/df) Pearson	=	1231.384

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

	<u>AIC</u>	=	9.959653
Log likelihood = -1686.16125	<u>BIC</u>	=	413013.1

shrelaw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.6230115	.7612097	0.82	0.413	-.868932	2.114955
_cons	26.21356	2.042278	12.84	0.000	22.21077	30.21635

```
1199 . glm HP2inthob shrelaw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 236.715
Iteration 2: deviance = 235.3689
Iteration 3: deviance = 235.3625
Iteration 4: deviance = 235.3625
```

Generalized linear models	No. of obs	=	339
Optimization : ML Fisher scoring	Residual df	=	337
(IRLS EIM)	Scale parameter	=	1
Deviance = 235.3625161	(1/df) Deviance	=	.6984051
Pearson = 339.597009	(1/df) Pearson	=	1.007706

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

	BIC	=	-1728
--	-----	---	-------

HP2inthob	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
shrelaw2	.0038952	.0020421	1.91	0.056	-.0001073	.0078976
_cons	-1.331337	.0990092	-13.45	0.000	-1.525391	-1.137282

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

```
1200 .
1201 . title4 "6. Summary matrix for dose - interests and hobbies impact"
```

```
6. Summary matrix for dose - interests and hobbies impact
```

```
1202 . *xx summary of mediating effects: males only age and illw2 2
1203 . *xx          females: age
1204 .
1205 .
1206 .
1207 . * summary of inthob moderator effects none
1208 . scalar inthobMedMw2 = "age "

1209 . scalar inthobMedFw2 = "age bf4 illw2 bf4m"

1210 .
1211 . * no sign main dose effect for males
1212 . * no male moderators
1213 . * 3 signif main effects in male main effect model
1214 .
1215 .
1216 . * no signif dose main effect for females
1217 . * 3 main female effects
1218 . * no significant female moderators
1219 . di _skip(4)
```

```

1220 . matrix define inthbMw2 = J(1,8, 0)

1221 .          matrix define inthbFw2 = J(1,8, 0)

1222 . matrix colnames inthbMw2= hypnum ptnum wave gender medsig numMASig numMods
    > ig numMed

1223 . matrix colnames inthbFw2= hypnum ptnum wave gender medsig numMASig numMods
    > ig numMed

1224 .          matrix define inthbMw2= (1, 2, 3, 1, 0, 3, 0, 1 )

1225 .          matrix define inthbFw2= (1, 2, 3, 2, 0, 3, 0, 4 )

1226 .          matrix rowname inthbMw2 = inthbM

1227 .          matrix rowname inthbFw2 = inthobF

1228 .          matlist inthbMw2

    > 6          |          c1          c2          c3          c4          c5          c
    >          c7          c8
    -----|-----
    >          |
    > inthbM    |          1          2          3          1          0
    > 3          |          0          1
    >          |

1229 .          matlist inthbFw2

    > 6          |          c1          c2          c3          c4          c5          c
    >          c7          c8
    -----|-----
    >          |
    > inthobF   |          1          2          3          2          0
    > 3          |          0          4
    >          |

1230 .          matrix define H1pt2w2 = ( wkMw2 \ wkFw2 \ hmcrMw2 \ hmcrFw2 \ s
    > pMw2 ///
    >          \ spFw2 \ prbfamMw2 \ prbfamFw2 \ sxlifeMw2 \ sxlifeFw2 \ inth
    > bMw2 \ inthbFw2)

```

1231 .

1232 . matlist H1pt2w2

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	2	1	0	
> 2	0	2					
	r1	1	2	2	2	0	
> 1	0	2					
	r1	1	2	3	1	0	
> 1	0	1					
	r1	1	2	3	2	1	
> 1	0	2					
	spMw2	1	2	3	1	0	
> 4	0	1					
	spFw2	1	2	3	2	1	
> 5	0	3					
	prbfamMw2	1	2	3	1	0	
> 3	0	1					
	prbfamFw2	1	2	3	2	0	
> 3	0	2					
	sxlifemw2	1	2	3	1	0	
> 6	0	1					
	sxlifefw2	1	2	3	2	0	
> 4	0	5					
	inthbM	1	2	3	1	0	
> 3	0	1					
	inthobF	1	2	3	2	0	
> 3	0	4					

1233 . matrix colnames H1pt2w2 = hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

1234 . matrix rownames H1pt2w2 = wkMw2 wkFw2 hmcrMw2 hmcrFw2 socprbMw2
> socprbFw2 prbfamMw2 prbfamFw2 sxlifemw2 sxlifefw2 inthbMw2 inthbFw2

		hypnum	ptnum	wave	gender	medsig	numMasi
> g	numModsig	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2	0	2					
	wkFw2	1	2	2	2	0	
> 1	0	2					
	hmcrMw2	1	2	3	1	0	
> 1	0	1					
	hmcrFw2	1	2	3	2	1	
> 1	0	2					
	socprbMw2	1	2	3	1	0	
> 4	0	1					
	socprbFw2	1	2	3	2	1	
> 5	0	3					
	prbfamMw2	1	2	3	1	0	
> 3	0	1					
	prbFamFw2	1	2	3	2	0	
> 3	0	2					
	sxlifeMw2	1	2	3	1	0	
> 6	0	1					
	sxlifeFw2	1	2	3	2	0	
> 4	0	5					
	inthbMw2	1	2	3	1	0	
> 3	0	1					
	inthbFw2	1	2	3	2	0	
> 3	0	4					

```
1236 .
1237 . title "7. h1 pt2 wave 2 Dose=> vacation plans impact analysis "xxxxxxxxxx
      > xxxxxxxxx
```

```
*****
> *
*****
> *
*****
> *
*****
> *
*****
7. h1 pt2 wave 2 Dose=> vacation plans impact analysis
> *
*****
> *
*****
> *
*****
```

```

> *
*****
> *
*****
17 Jun 2012    10:10:14    ****
> *
*****
> *
*****
> *

```

```

1238 .
1239 .
1240 .
1241 . cap gen hp2vactn = HP2vacatn

1242 .
1243 . forvalues j = 2/2 {
      2. title " H1 pt 2 Wave 2 Dose = >    hp2vactn main effects models"
      3. set more off
      4. local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
      5. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      6. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      7. di _skip(3)
      8.
1244 . di as input "Male model Wave 2 dose-hp2vactn moderator model "
      9. di _skip(4)
     10. xi: logistic hp2vactn age i.educ occ1w`j'-occ8w`j' ///
>   marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' ///
>   radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>   deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>   illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' suchrw`j' havmil
> sq ///
>   radhlw`j' avgcumdosew`j' if gender==1, coef
     11. di _skip(4)
     12. title3 "trimmed hp2vactn main effects models for H1 no direct dose effec
> t for male"
     13. pwcorr hp2hmcare age deaw2 shjobw2 bf7m shjobw2 havmilsq ///
>   radhlw2 avgcumdosew1 if gender==1, sig obs sidak star(.05) listwise
     14. di _skip(1)
     15. di as input "For males hp2vactn wave3 and d2 is not signif "
     16. di _skip(1)
     17. logistic hp2vactn age deaw2 shjobw2 bf7m havmilsq ///
>   radhlw2 avgcumdosew1 if ///
>   gender==1, coef
     18. }

```


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

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

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

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

note: dvcew2 != 0 predicts failure perfectly
 dvcew2 dropped and 2 obs not used

note: _Ieduc_6 omitted because of collinearity

note: bf15 omitted because of collinearity

note: radhlw2 omitted because of collinearity

note: avgcumdosew2 omitted because of collinearity

Logistic regression	Number of obs	=	226
	LR chi2(34)	=	89.37
	Prob > chi2	=	0.0000
Log likelihood = -56.061123	Pseudo R2	=	0.4435

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0518481	.0320007	1.62	0.105	-.0108721	.1145682
_Ieduc_2	-.8995561	1.385138	-0.65	0.516	-3.614377	1.815265
_Ieduc_3	-.9705268	.7645926	-1.27	0.204	-2.469101	.5280471
_Ieduc_4	0	(omitted)				
_Ieduc_5	.2832276	.9129115	0.31	0.756	-1.506046	2.072501
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	.8106927	4.39778	0.18	0.854	-7.808798	9.430184
occ2w2	.6920438	4.410202	0.16	0.875	-7.951794	9.335881
occ3w2	.1305127	4.486304	0.03	0.977	-8.662482	8.923507
occ4w2	.89698	4.456507	0.20	0.840	-7.837613	9.631573
occ5w2	2.521801	4.487812	0.56	0.574	-6.274149	11.31775
occ6w2	0	(omitted)				
occ7w2	-.3588464	4.557173	-0.08	0.937	-9.290741	8.573048
occ8w2	0	(omitted)				
marrw21	-2.421712	1.8269	-1.33	0.185	-6.002369	1.158946
marrw22	0	(omitted)				
marrw23	-3.630848	1.854766	-1.96	0.050	-7.266123	.0044279
marrw25	0	(omitted)				
marrw26	0	(omitted)				

inclw2	0	(omitted)				
inc2w2	1.85842	4.404089	0.42	0.673	-6.773436	10.49027
inc3w2	2.742231	4.406664	0.62	0.534	-5.894672	11.37913
inc4w2	0	(omitted)				
radhlw2	.0040453	.0113057	0.36	0.720	-.0181135	.0262041
havmil	.0057124	.0149305	0.38	0.702	-.0235508	.0349756
avgcumdosew2	-.2290056	.2971244	-0.77	0.441	-.8113587	.3533474
bf1	-.0014462	.0165487	-0.09	0.930	-.0338809	.0309886
bf4	-.3542988	.0849763	-4.17	0.000	-.5208492	-.1877483
bf6	.0330318	.0142347	2.32	0.020	.0051324	.0609312
bf7	.138525	.1284222	1.08	0.281	-.1131778	.3902278
bf14	-.0001823	.0001057	-1.72	0.085	-.0003895	.0000249
bf15	0	(omitted)				
bf40	.7151656	.2261712	3.16	0.002	.2718781	1.158453
deaw2	-.1293481	.4547459	-0.28	0.776	-1.020634	.7619374
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	.6561002	.566831	1.16	0.247	-.4548681	1.767069
movew2	.8988969	.8083424	1.11	0.266	-.6854251	2.483219
illw2	-.1907347	.4011558	-0.48	0.634	-.9769857	.5955162
shfamw2	.0075499	.0104385	0.72	0.470	-.0129092	.0280089
shhlw2	-.0086364	.01369	-0.63	0.528	-.0354682	.0181955
shjobw2	-.0142832	.0135576	-1.05	0.292	-.0408556	.0122892
shrelaw2	-.0233172	.0117345	-1.99	0.047	-.0463164	-.000318
suprtw2	.0076256	.010193	0.75	0.454	-.0123524	.0276036
suchrw2	-.0031525	.0091098	-0.35	0.729	-.0210073	.0147023
havmilsq	-.00002	.0000344	-0.58	0.560	-.0000874	.0000473
radhlw2	0	(omitted)				
avgcumdosew2	0	(omitted)				
_cons	-2.643954	3.239572	-0.82	0.414	-8.993397	3.70549

Note: 1 failure and 0 successes completely determined.

```

title3 : trimmed hp2vactn main effects models for H1 no direct dose effect for
> male
17 Jun 2012
10:10:16
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/hltests
> /hlpt2
Data file chwide16june2012.dta currently has 2392 variables and 703 obs
> ervations

```

	hp2hmc~e	age	deaw2	shjobw2	bf7m	shjobw2	havmilsq
hp2hmcare	1.0000						
	340						
age	0.2761*	1.0000					
	0.0000						
	340	340					
deaw2	0.0240	0.2906*	1.0000				
	1.0000	0.0000					
	340	340	340				
shjobw2	0.0806	0.0604	-0.0188	1.0000			
	0.9953	1.0000	1.0000				
	340	340	340	340			
bf7m	-0.1339	-0.0182	0.1279	0.0160	1.0000		
	0.3860	1.0000	0.4863	1.0000			
	340	340	340	340	340		
shjobw2	0.0806	0.0604	-0.0188	1.0000*	0.0160	1.0000	
	0.9953	1.0000	1.0000	0.0000	1.0000		
	340	340	340	340	340	340	
havmilsq	-0.0347	0.0207	-0.0098	-0.0082	-0.0420	-0.0082	1.0000
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
	340	340	340	340	340	340	340
radhlw2	0.2793*	0.3358*	-0.0218	0.2249*	0.1098	0.2249*	-0.0846
	0.0000	0.0000	1.0000	0.0010	0.7946	0.0010	0.9898
	340	340	340	340	340	340	340
avgcumdosew1	0.0010	0.0918	0.0232	0.0706	0.0206	0.0706	-0.0345
	1.0000	0.9680	1.0000	0.9996	1.0000	0.9996	1.0000
	340	340	340	340	340	340	340

	radhlw2 avgcum~1	
radhlw2	1.0000	
	340	
avgcumdosew1	0.0826	1.0000
	0.9929	
	340	340

For males hp2vactn wave3 and d2 is not signif

Logistic regression	Number of obs	=	340
	LR chi2(7)	=	40.46
	Prob > chi2	=	0.0000
Log likelihood = -104.92462	Pseudo R2	=	0.1616

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0623584	.0170238	3.66	0.000	.0289924	.0957244
deaw2	-.1196817	.316188	-0.38	0.705	-.7393988	.5000354
shjobw2	.0033867	.0046422	0.73	0.466	-.0057118	.0124853
bf7m	-.0003419	.0002442	-1.40	0.161	-.0008205	.0001367
havmilsq	-5.89e-06	7.80e-06	-0.75	0.451	-.0000212	9.41e-06
radhlw2	.0148258	.0055784	2.66	0.008	.0038923	.0257592
avgcumdosew1	-.069755	.1488625	-0.47	0.639	-.36152	.2220101
_cons	-5.869014	1.014681	-5.78	0.000	-7.857752	-3.880275

```

1245 .
1246 . scalar SigDoseVactnMw2 = "no"

1247 . scalar MainEffVactnMw2 = "age radhlw2 "
```


> *

```
1261 . di as input "No sig main male dose main effects model"
      No sig main male dose main effects model
```

```
1262 . sw, pr(.1): logit hp2vacatn `myvarlist' if gender==1
              begin with full model
p = 0.7050 >= 0.1000 removing deaw2
p = 0.6331 >= 0.1000 removing avgcumdosew1
p = 0.4916 >= 0.1000 removing shjobw2
p = 0.4627 >= 0.1000 removing havmilsq
p = 0.1243 >= 0.1000 removing bf7m
```

Logistic regression	Number of obs	=	340
	LR chi2(2)	=	36.09
	Prob > chi2	=	0.0000
Log likelihood = -107.10862	Pseudo R2	=	0.1442

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0587352	.0156958	3.74	0.000	.027972	.0894984
radhlw2	.0163217	.005398	3.02	0.002	.0057417	.0269016
_cons	-6.0454	.8953448	-6.75	0.000	-7.800244	-4.290557

```
1263 .
1264 .
1265 . local cn8:colnames(e(b))

1266 . di "`cn8'"
      age radhlw2 _cons

1267 . local len8 = length("`cn8'")
```

```

1268 . di `len7'
      58

1269 . local len8b = `len8' - 6

1270 . di `len8b'
      11

1271 . local myvarlist = substr("`cn8'",1,`len8b')

1272 . di "`myvarlist'"
      age radhlw2

1273 .
1274 . logit hp2vacatn age radhlw2 avgcumdosew2 ageXd2 radhlw2Xd2 if gender==1

```

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -109.21801
Iteration 2:  log likelihood = -106.67525
Iteration 3:  log likelihood = -106.57547
Iteration 4:  log likelihood = -106.5735
Iteration 5:  log likelihood = -106.5735

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	37.16
	Prob > chi2	=	0.0000
Log likelihood = -106.5735	Pseudo R2	=	0.1485

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0665329	.0222738	2.99	0.003	.022877	.1101887
radhlw2	.0125498	.0074393	1.69	0.092	-.0020309	.0271304
avgcumdosew2	.1747054	1.332435	0.13	0.896	-2.436818	2.786229
ageXd2	-.0112359	.0243435	-0.46	0.644	-.0589483	.0364764
radhlw2Xd2	.005418	.0075235	0.72	0.471	-.0093278	.0201638
_cons	-6.162813	1.25139	-4.92	0.000	-8.615492	-3.710135

```

1275 .
1276 .   title "Trimmed male wave 2 interaction dose=> vacation plans model"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****      Trimmed male wave 2 interaction dose=> vacation plans model      *****
> *
*****
> *
*****
> *
*****
> *
*****      17 Jun 2012      10:10:28      *****
> *
*****
> *
*****
> *

```

```

1277 .   logit hp2vacatn age radhlw2 ageXd2 bf7m avgcumdosew2 bf4m bf4mXd2 bf7mXd2 i
> f gender==1

```

```

Iteration 0:   log likelihood = -125.15243
Iteration 1:   log likelihood = -103.6908
Iteration 2:   log likelihood = -95.548287
Iteration 3:   log likelihood = -94.791601
Iteration 4:   log likelihood = -94.72809
Iteration 5:   log likelihood = -94.72726
Iteration 6:   log likelihood = -94.727259

```

Logistic regression	Number of obs	=	340
	LR chi2(8)	=	60.85
	Prob > chi2	=	0.0000
Log likelihood = -94.727259	Pseudo R2	=	0.2431

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0748804	.0361789	2.07	0.038	.003971	.1457898
radhlw2	.000021	.0067408	0.00	0.998	-.0131908	.0132328
ageXd2	-.0497686	.0503553	-0.99	0.323	-.1484632	.0489259
bf7m	.0001854	.0004234	0.44	0.661	-.0006444	.0010153
avgcumdosew2	4.201192	4.071901	1.03	0.302	-3.779588	12.18197
bf4m	-.1121478	.0674199	-1.66	0.096	-.2442883	.0199927
bf4mXd2	-.0946542	.0750285	-1.26	0.207	-.2417073	.0523988
bf7mXd2	.0002633	.0003512	0.75	0.453	-.0004251	.0009517
_cons	-4.20268	2.927797	-1.44	0.151	-9.941058	1.535697

Note: 1 failure and 0 successes completely determined.

```

1278 .
1279 . scalar vactnModMw2 ="none"

1280 .
1281 . title4 "Trimmed Female model Wave 2 main effects dose-hp2vacatn model "

```

Trimmed Female model Wave 2 main effects dose-hp2vacatn model

```

1282 . forvalues j = 2/2 {
      2. local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40
      3.
1283 . xi: logistic hp2vacatn age radhlw`j' avgcumdosew`j' ///
      > deaw`j' suchrw`j' ///
      > if gender==2, coef diffcult iterate(50)
      4.
1284 . }

```

Logistic regression	Number of obs	=	363
	LR chi2(5)	=	70.03
	Prob > chi2	=	0.0000
Log likelihood = -132.50308	Pseudo R2	=	0.2090

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0851818	.0154813	5.50	0.000	.054839	.1155246
radhlw2	.0170145	.0053804	3.16	0.002	.0064692	.0275599
avgcumdosew2	.0786711	.0879844	0.89	0.371	-.0937752	.2511173
deaw2	.201149	.1681372	1.20	0.232	-.1283938	.5306918
suchrw2	-.0020193	.0038609	-0.52	0.601	-.0095866	.005548
_cons	-7.431055	.9998597	-7.43	0.000	-9.390744	-5.471366

```

1285 .
1286 . sw, pr(.1): logit hp2vactn age radhlw2 avgcumdosew2 havmilsq ageXd2 radhlw2X
    > d2 if gender==2

```

```

                                begin with full model
p = 0.7449 >= 0.1000 removing radhlw2Xd2
p = 0.7297 >= 0.1000 removing havmilsq
p = 0.4685 >= 0.1000 removing ageXd2
p = 0.4486 >= 0.1000 removing avgcumdosew2

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(2)      =       67.78
                                                    Prob > chi2     =       0.0000
Log likelihood =   -133.624                      Pseudo R2       =       0.2023

```

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.087459	.0153711	5.69	0.000	.0573321	.1175858
radhlw2	.0183043	.0051588	3.55	0.000	.0081933	.0284153
_cons	-7.552753	.9504531	-7.95	0.000	-9.415607	-5.689899

```

1287 .
1288 .
1289 .
1290 . scalar SigDoseVactnMw2 = "no"

1291 . scalar MainEffVactnMw2 = "age radhlw2"

1292 . scalar VactnModMw2 = "none"

1293 .
1294 . * summary of male moderating effects: no sign main dose effect in main effe
    > cts model
1295 . *          no signif male moderators
1296 . *          3 significant main effects in main effects model
1297 .

```

```

1298 . * summary of female moderation main effects: no signif main dose effect
1299 .
1300 .
1301 . scalar SigDoseVactnFw2 = "no"

1302 . scalar MainEffVactnFw2 = "age radhlw2 bf7m"

1303 .
1304 . cap gen suchrw2Xd2 = suchrw2*avgcumdosew2

1305 .
1306 .
1307 . scalar VacatnModFw2 = "none"

1308 . *xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
    > xxxx
1309 . cap gen hp2vactn = HP2vacatn

1310 . title4 "Male mediator tests for vacation plans impact of dose"

```

```

Male mediator tests for vacation plans impact of dose

```

```

1311 . * for males
1312 .
1313 . * age is a mediator for males
1314 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
1315 . 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.)

```
1316 .
```

```
1317 .
1318 . des illw2
```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```
1319 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-303.59609**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew2	.0085423	.0128556		0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406		7.96	0.000	.2066336	.3416382

```
1320 . glm hp2vactn illw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

Iteration 1: deviance = **246.5506**
 Iteration 2: deviance = **245.3093**
 Iteration 3: deviance = **245.3029**
 Iteration 4: deviance = **245.3029**
 Iteration 5: deviance = **245.3029**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 245.3029322	(1/df) Deviance	=	.7257483
Pearson = 335.4909761	(1/df) Pearson	=	.9925769

[Bernoulli]
[Probit]

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.3031606	.1114242	2.72	0.007	.0847731	.5215481
_cons	-1.277579	.0863769	-14.79	0.000	-1.446875	-1.108284

```
1321 .
1322 . des radhlw2
```

```
1323 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Generalized linear models
Optimization : ML

No. of obs	=	340
Residual df	=	338
Scale parameter	=	1247.933
(1/df) Deviance	=	1247.933
(1/df) Pearson	=	1247.933

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

[Gaussian]
[Identity]

Log likelihood = -1693.407647

AIC = 9.972986
BIC = 419831.3

	OIM					
radhlw2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

```
1324 . glm hp2vactn radhlw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 234.5448
Iteration 2:  deviance = 229.6041
Iteration 3:  deviance = 229.4465
Iteration 4:  deviance = 229.4462
Iteration 5:  deviance = 229.4462
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  MQL Fisher scoring  Residual df    =       338
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 229.4462113         (1/df) Deviance =  .6788349
Pearson           = 340.4683102         (1/df) Pearson  =  1.007303
```

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

```
BIC = -1740.737
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0116586	.0021811	5.35	0.000	.0073837	.0159334
_cons	-1.817407	.1519393	-11.96	0.000	-2.115203	-1.519612

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

```
1325 .
1326 . * for females
1327 .
1328 . * age is a mediator for females
1329 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

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

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

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

```
Log likelihood = -1406.940271      AIC = 7.762756
                                   BIC = 47299.65
```

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

```
1330 . 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 : ML 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.)

```
1331 .
```

```

1332 . * illness is a mediating effect for females = > vacatn
1333 . des illw2

```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```

1334 . glm illw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

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

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

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

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

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

```

1335 . glm hp2vactn illw2 if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **329.874**
 Iteration 2: deviance = **329.8007**
 Iteration 3: deviance = **329.8005**
 Iteration 4: deviance = **329.8005**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 329.8005369	(1/df) Deviance	=	.9135749
Pearson = 363.0908863	(1/df) Pearson	=	1.005792

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1798.079

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.1861547	.0776301	2.40	0.016	.0340026	.3383068
_cons	-1.027515	.0837109	-12.27	0.000	-1.191586	-.8634451

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

1336 .
 1337 . * radhlw2 is a mediating effect for females => vactn
 1338 . des radhlw2

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		Self-perceived Chornobyl health threat in Wave 2

1339 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1791.2233

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

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

	AIC	=	9.880018
Log likelihood = -1791.223306	BIC	=	408533.7

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

```
1340 . glm hp2vactn radhlw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 310.7426
Iteration 2:  deviance = 307.9144
Iteration 3:  deviance = 307.878
Iteration 4:  deviance = 307.878
Iteration 5:  deviance = 307.878
```

```
Generalized linear models                      No. of obs      =       363
Optimization      :  MQL Fisher scoring        Residual df     =       361
                   (IRLS EIM)                  Scale parameter =         1
Deviance          = 307.8780006                (1/df) Deviance =  .8528476
Pearson           = 369.926962                 (1/df) Pearson  = 1.024728
```

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

```
BIC = -1820.001
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0127779	.0023866	5.35	0.000	.0081002	.0174555
_cons	-1.793767	.1848064	-9.71	0.000	-2.15598	-1.431553

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

```
1341 .
1342 . * summary of male moderating effects: no sign main dose effect in main effe
> cts model
1343 . *          no signif male moderators
1344 . *          3 significant main effects in main effects model
1345 . * summary omnibus model
1346 . des radhlw2
```

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		Self-perceived Chernobyl health threat in Wave 2

```
1347 . glm radhlw2 avgcumdosew2 illw2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1788.7036
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	360
	Scale parameter	=	1125
Deviance = 404999.9575	(1/df) Deviance	=	1125
Pearson = 404999.9575	(1/df) Pearson	=	1125

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

	<u>AIC</u>	=	9.871645
Log likelihood = -1788.70364	<u>BIC</u>	=	402878

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	2.733328	1.30167	2.10	0.036	.1821022	5.284554
illw2	4.552	2.029125	2.24	0.025	.5749882	8.529013
_cons	55.58022	2.186381	25.42	0.000	51.29499	59.86544

```
1348 . glm hp2vactn radhlw2 illw2 avgcumdosew2 if gender==2, fam(bin) irls scale(de > v) link(probit)
```

```
Iteration 1: deviance = 306.8282
Iteration 2: deviance = 303.8899
Iteration 3: deviance = 303.8448
Iteration 4: deviance = 303.8448
Iteration 5: deviance = 303.8448
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 303.8447923	(1/df) Deviance	=	.8463643
Pearson = 365.1970108	(1/df) Pearson	=	1.017262

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

	BIC	=	-1812.246
--	-----	---	-----------

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0120672	.0024098	5.01	0.000	.007344	.0167903
illw2	.1173614	.0786613	1.49	0.136	-.036812	.2715347
avgcumdosew2	.0586976	.047942	1.22	0.221	-.035267	.1526623
_cons	-1.859623	.1874026	-9.92	0.000	-2.226926	-1.492321

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

```

1349 .
1350 .
1351 . scalar VactnMedMw2 = "age"

1352 . scalar VactnMedFw2 = "age illw2 radhlw2"

1353 .
1354 . *xx summary of moderator effects for females:
1355 .   * no signif main dose effect
1356 .   * 3 signif main effects in main effect model
1357 .   * 1 moderator: deaw2Xd2
1358 . title4 "7. Summary Matrix construction of dose - vacatn plans impact"

```

```

7. Summary Matrix construction of dose - vacatn plans impact

```

```

1359 .
1360 .   matrix define   vactnMw2 = J(1,8, 0)

1361 .           matrix define   vactnFw2 = J(1,8, 0)

1362 . matrix colnames   vactnMw2=   hypnum ptnum wave gender medsig numMASig numMods
> ig numMed

1363 . matrix colnames   vactnFw2=   hypnum ptnum wave gender medsig numMASig numMods
> ig numMed

```

```
1364 .      matrix define  vactnMw2= (1, 2, 3, 1, 0, 2, 0, 1 )
```

```
1365 .      matrix define  vactnFw2= (1, 2, 3, 2, 0, 3, 0, 3 )
```

```
1366 .      matrix rowname  vactnMw2 =  vactnM
```

```
1367 .      matrix rowname  vactnFw2 =  vactnF
```

```
1368 .      matlist  vactnMw2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	vactnM	1	2	3	1	0	
> 2	0	1					

```
1369 .      matlist  vactnFw2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	vactnF	1	2	3	2	0	
> 3	0	3					

```
1370 .      matrix define H1pt2w2 = ( wkMw2 \ wkFw2 \ hmcrMw2 \ hmcrFw2 \ s
> pMw2 ///
> \ spFw2 \ sxlifeMw2 \ sxlifeFw2 \ inthbMw2 \ inthbFw2 \ vactn
> Mw2 \ vactnFw2 )
```

```
1371 .
```

```
1372 .      matlist H1pt2w2
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	2	1	0	
> 2	0	2					
	r1	1	2	2	2	0	
> 1	0	2					
	r1	1	2	3	1	0	
> 1	0	1					
	r1	1	2	3	2	1	
> 1	0	2					
	spMw2	1	2	3	1	0	
> 4	0	1					
	spFw2	1	2	3	2	1	

```

> 5      0      3
    sxlifeMw2 |      1      2      3      1      0
> 6      0      1
    sxlifeFw2 |      1      2      3      2      0
> 4      0      5
    inthbM |      1      2      3      1      0
> 3      0      1
    inthobF |      1      2      3      2      0
> 3      0      4
    vactnM |      1      2      3      1      0
> 2      0      1
    vactnF |      1      2      3      2      0
> 3      0      3

```

```

1373 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

```

```

1374 .      matrix rownames H1pt2w2 =      wkMw2  wkFw2  hmcrMw2  hmcrFw2  socprbMw2
> socprbFw2  inthbMw2  inthbFw2  vactnMw2  vacatnFw2

```

```

1375 .      matlist H1pt2w2

```

		hypnum	ptnum	wave	gender	medsig	numMA si
> g	numModsig	numMed					
>							
	wkMw2	1	2	2	1	0	
> 2		0	2				
	wkFw2	1	2	2	2	0	
> 1		0	2				
	hmcrMw2	1	2	3	1	0	
> 1		0	1				
	hmcrFw2	1	2	3	2	1	
> 1		0	2				
	socprbMw2	1	2	3	1	0	
> 4		0	1				
	socprbFw2	1	2	3	2	1	
> 5		0	3				
	inthbMw2	1	2	3	1	0	
> 6		0	1				
	inthbFw2	1	2	3	2	0	
> 4		0	5				
	vactnMw2	1	2	3	1	0	
> 3		0	1				
	vacatnFw2	1	2	3	2	0	
> 3		0	4				
	vacatnFw2	1	2	3	1	0	
> 2		0	1				
	vacatnFw2	1	2	3	2	0	

> 3 0 3

```

1376 .      scalar list
      VactnMedMw2 = age
      MainEffVactnMw2 = age radhlw2
      sxlifeMedMw2 = age illw2
      SigDoseSxlifeFw2 = no
      MainEffsxlifeFw2 = age radhlw2 bf4 bf4m
      MainEffPrbsocMw2 = age radhlw2 shjobw2
      MainEffhmcrFw2 = age
      hmcrMedFw2 = age bf4
      MainEffwkFw2 = age
      MainEffwkMw2 = age
      inthobMedMw2 = age
      inthobMw2 = age
      PrbfmhmModMw2 = none
      MainEffProbSocFw2 = age radhlw2 avgcumdosew2 bf4
      hmcrModMw2 = none
      MainEffhmcrMw2 = age
      wkMedFw2 = age b4
      wkMedMw2 = age bf4
      MainEffsxlifeMw2 = age bf4 bf40 shjobw2 shrelaw2 radhlw2
      MainEffPrbfmhmMw2 = bf4 bf6 bf7
      ProbsocMedFw2 = age bf4 radhlw2
      hmcareMedFw2 = age bf4
      WkhmcrMw2 = age b4
      MainEffhmcrw2 = age
      hmcrModFw2 = none
      SigDoseHmcrFw2 = yes
      NumhmcrModMw2 = none
      SigDosehmcrMw2 = no
      SigdosehmcrFw2 = yes
      hmcrMedMw2 = age ageXillw2
      SigDosehmcrFw2 = no
      MainEffhmcareMw2 = age
      WkMedMw2 = age ageXillw2
      wkMedFw3 = radhlw3 age ageXillw3 bf40 bf4m bf1
      VactnMedFw2 = age illw2 radhlw2
      VacatnModFw2 = none
      MainEffVactnFw2 = age radhlw2 bf7m
      SigDoseVactnFw2 = no
      VactnModMw2 = none
      vactnModMw2 = none
      SigDoseVactnMw2 = no
      inthobMedFw2 = age bf4 illw2 bf4m
      InthbModFw2 = none
      MainEffInthbFw2 = age radhlw2 bf4
      SigdoseInthbFw2 = no
      InthbModMw2 = none

```

```

MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
MainEffMw2 = radhlw2 bf4 bf40
SigdoseMEinthob = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
SxLifeModFw2 = no
sxlifeModFw2 = none
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf4 bf6 bf7
ProbsocMedMw2 = age
ProbsocModFw2 = none
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
PrbsocModMw2 = none
SigdoseMw2 = none
hmcareMedMw2 = age
hmcareModFw2 = none
MainEffhmcarew2 = age
SigdoseHmcareFw2 = no
hmcareModMw2 = none
SigDoseHmcareMw2 = no
NameMedMw2 = age ageXillw2
  NumModMw2 = none
SigDosehmcareMw2 = no
SigDoseWKMw2 = no
  WkMedFw2 = age bf4
  WkModFw2 = none
  WKModMw2 = none
SigDoseWkMw2 = no
SigDoseWkFw2 = no
SigDoseFw2 = no
  wkModFw2 = none
  wkModMw2 = none
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
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no

```

```
1377 . pwd
      /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2

1378 . di c(filename)
      chwide16june2012.dta

1379 .
1380 . sjlog close, replace
```