

```

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: 18 Jun 2012 18:10:41
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 1 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=1/1 {
      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
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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)


```

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 ///
>          radhlw`j' bf1 bf20 ///
>          deaw`j' ///
>          shhlw`j' shjobw`j' shrelaw`j' suprtw`j' ///
>          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= 1

chunk 2 H1 test:Gender= 1 model Wave = 1 for hp2vactn

Full Nottingham Part 2 HP2work subscale models

Logistic regression	Number of obs	=	340
	LR chi2(9)	=	31.46
	Prob > chi2	=	0.0002
Log likelihood = -157.14168	Pseudo R2	=	0.0910

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0308396	.0127975	2.41	0.016	.005757	.0559223
radhlw1	.0011812	.0045458	0.26	0.795	-.0077284	.0100908
bf1	-.0366332	.0469292	-0.78	0.435	-.1286127	.0553463
bf20	.0453017	.0444164	1.02	0.308	-.0417528	.1323562
deaw1	-.0051463	.2892671	-0.02	0.986	-.5720994	.5618067
shhlw1	.0001023	.0055692	0.02	0.985	-.0108131	.0110176
shjobw1	.0091313	.0050059	1.82	0.068	-.0006801	.0189427
shrelaw1	.0025607	.0044585	0.57	0.566	-.0061777	.0112992
suprtw1	.0026986	.0050591	0.53	0.594	-.0072171	.0126143
_cons	-5.679852	1.827319	-3.11	0.002	-9.261332	-2.098372

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	3	4	7
-	67	266	333
Total	70	270	340

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

Sensitivity	$\Pr(+ D)$	4.29%
Specificity	$\Pr(- \sim D)$	98.52%
Positive predictive value	$\Pr(D +)$	42.86%
Negative predictive value	$\Pr(\sim D -)$	79.88%
False + rate for true ~D	$\Pr(+ \sim D)$	1.48%
False - rate for true D	$\Pr(- D)$	95.71%
False + rate for classified +	$\Pr(\sim D +)$	57.14%
False - rate for classified -	$\Pr(D -)$	20.12%
Correctly classified		79.12%

Logistic model for HP2work, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      333
      Pearson chi2(323) =      339.90
          Prob > chi2 =      0.2483
  
```

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

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-157.142
D(330):	314.283	LR(9):	31.462
		Prob > LR:	0.000
McFadden's R2:	0.091	McFadden's Adj R2:	0.033
Maximum Likelihood R2:	0.088	Cragg & Uhler's R2:	0.138
McKelvey and Zavoina's R2:	0.183	Efron's R2:	0.092
Variance of y*:	4.026	Variance of error:	3.290
Count R2:	0.791	Adj Count R2:	-0.014
AIC:	0.983	AIC*n:	334.283
BIC:	-1609.269	BIC':	20.998

Full main model for HP2work for wave= 1

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

Full Nottingham Part 2 HP2work subscale models

Logistic regression	Number of obs	=	361
	LR chi2(9)	=	47.56
	Prob > chi2	=	0.0000
Log likelihood = -182.19002	Pseudo R2	=	0.1154

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0643256	.0124013	5.19	0.000	.0400194	.0886317
radhlw1	.0047546	.0039694	1.20	0.231	-.0030253	.0125344
bf1	.0004355	.0252089	0.02	0.986	-.0489731	.049844
bf20	.0056912	.0216782	0.26	0.793	-.0367972	.0481796
deawl	-.1112272	.1659119	-0.67	0.503	-.4364086	.2139542
shhlw1	.0037005	.0053166	0.70	0.486	-.0067199	.0141209
shjobw1	.0025496	.0049315	0.52	0.605	-.0071159	.0122152
shrelaw1	-.0059036	.0043278	-1.36	0.173	-.0143859	.0025787
suprtw1	.0007605	.0038753	0.20	0.844	-.006835	.008356
_cons	-5.262441	1.017784	-5.17	0.000	-7.257261	-3.26762

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	24	12	36
-	69	256	325
Total	93	268	361

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	25.81%
Specificity	$\Pr(- \sim D)$	95.52%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	78.77%
False + rate for true ~D	$\Pr(+ \sim D)$	4.48%
False - rate for true D	$\Pr(- D)$	74.19%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	21.23%
Correctly classified		77.56%

Logistic model for HP2work, goodness-of-fit test

```

      number of observations =      361
number of covariate patterns =      359
      Pearson chi2(349) =      374.34
              Prob > chi2 =      0.1680

```

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

Log-Lik Intercept Only:	-205.969	Log-Lik Full Model:	-182.190
D(351):	364.380	LR(9):	47.557
		Prob > LR:	0.000
McFadden's R2:	0.115	McFadden's Adj R2:	0.067
Maximum Likelihood R2:	0.123	Cragg & Uhler's R2:	0.181
McKelvey and Zavoina's R2:	0.198	Efron's R2:	0.141
Variance of y*:	4.100	Variance of error:	3.290
Count R2:	0.776	Adj Count R2:	0.129
AIC:	1.065	AIC*n:	384.380
BIC:	-1702.616	BIC':	5.443

Full main model for HP2hmcare for wave= 1

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

Full Nottingham Part 2 HP2hmcare subscale models

Logistic regression	Number of obs	=	340
	LR chi2(9)	=	46.85
	Prob > chi2	=	0.0000
Log likelihood = -149.44808	Pseudo R2	=	0.1355

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.052336	.0131829	3.97	0.000	.026498	.0781739
radhlw1	.0043343	.0047058	0.92	0.357	-.0048889	.0135576
bf1	-.0149427	.033119	-0.45	0.652	-.0798548	.0499693
bf20	.0144084	.0298855	0.48	0.630	-.0441661	.0729829
deaw1	-.1108583	.2961578	-0.37	0.708	-.6913169	.4696004
shhlw1	.0046663	.0057067	0.82	0.414	-.0065187	.0158513
shjobw1	.0132629	.0053838	2.46	0.014	.0027109	.023815
shrelaw1	-.0051278	.0047295	-1.08	0.278	-.0143976	.0041419
suprtw1	-.0070556	.0059804	-1.18	0.238	-.018777	.0046658
_cons	-5.506222	1.326203	-4.15	0.000	-8.105532	-2.906912

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	15	6	21
-	55	264	319
Total	70	270	340

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

Sensitivity	$\Pr(+ D)$	21.43%
Specificity	$\Pr(- \sim D)$	97.78%
Positive predictive value	$\Pr(D +)$	71.43%
Negative predictive value	$\Pr(\sim D -)$	82.76%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	2.22%
False - rate for true D	$\Pr(- D)$	78.57%
False + rate for classified +	$\Pr(\sim D +)$	28.57%
False - rate for classified -	$\Pr(D -)$	17.24%

Correctly classified	82.06%
----------------------	---------------

Logistic model for HP2hmcare, goodness-of-fit test

number of observations =	340
number of covariate patterns =	333
Pearson $\chi^2(323)$ =	340.89
Prob > χ^2 =	0.2365

Measures of Fit for **logit** of HP2hmcare

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-149.448
D(330):	298.896	LR(9):	46.850
		Prob > LR:	0.000
McFadden's R2:	0.136	McFadden's Adj R2:	0.078
Maximum Likelihood R2:	0.129	Cragg & Uhler's R2:	0.202
McKelvey and Zavoina's R2:	0.237	Efron's R2:	0.150
Variance of y^* :	4.310	Variance of error:	3.290
Count R2:	0.821	Adj Count R2:	0.129
AIC:	0.938	AIC*n:	318.896
BIC:	-1624.656	BIC':	5.611

Full main model for HP2hmcare for wave= 1

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

Full Nottingham Part 2 HP2hmcare subscale models

Logistic regression

Number of obs = 361

LR chi2(9) = 81.82

Prob > chi2 = 0.0000

Log likelihood = -191.97101

Pseudo R2 = 0.1757

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0920059	.0127833	7.20	0.000	.0669511	.1170607
radhlw1	.0020253	.0038466	0.53	0.599	-.0055139	.0095645
bf1	-.00663	.0212107	-0.31	0.755	-.0482022	.0349423
bf20	-.0001616	.0177132	-0.01	0.993	-.0348789	.0345556
deawl	-.084969	.1571368	-0.54	0.589	-.3929515	.2230135
shhlw1	-.0017213	.0052283	-0.33	0.742	-.0119686	.0085261
shjobw1	.0107311	.0048545	2.21	0.027	.0012164	.0202457
shrelaw1	-.0074675	.0042372	-1.76	0.078	-.0157724	.0008373
suprtw1	-.0008664	.0038272	-0.23	0.821	-.0083676	.0066348
_cons	-5.472133	.9016353	-6.07	0.000	-7.239306	-3.70496

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	62	28	90
-	63	208	271
Total	125	236	361

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

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	49.60%
Specificity	$\Pr(- \sim D)$	88.14%
Positive predictive value	$\Pr(D +)$	68.89%
Negative predictive value	$\Pr(\sim D -)$	76.75%
False + rate for true ~D	$\Pr(+ \sim D)$	11.86%
False - rate for true D	$\Pr(- D)$	50.40%
False + rate for classified +	$\Pr(\sim D +)$	31.11%
False - rate for classified -	$\Pr(D -)$	23.25%
Correctly classified		74.79%

Logistic model for HP2hmcare, goodness-of-fit test

```

      number of observations =      361
number of covariate patterns =      359
      Pearson chi2(349) =      375.75
      Prob > chi2 =      0.1555

```

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

Log-Lik Intercept Only:	-232.881	Log-Lik Full Model:	-191.971
D(351):	383.942	LR(9):	81.821
		Prob > LR:	0.000
McFadden's R2:	0.176	McFadden's Adj R2:	0.133
Maximum Likelihood R2:	0.203	Cragg & Uhler's R2:	0.280
McKelvey and Zavoina's R2:	0.288	Efron's R2:	0.223
Variance of y*:	4.623	Variance of error:	3.290
Count R2:	0.748	Adj Count R2:	0.272
AIC:	1.119	AIC*n:	403.942
BIC:	-1683.054	BIC':	-28.821

Full main model for HP2probsoc for wave= 1

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

Full Nottingham Part 2 HP2probsoc subscale models

Logistic regression	Number of obs	=	340
	LR chi2(9)	=	66.20
	Prob > chi2	=	0.0000
Log likelihood = -92.051568	Pseudo R2	=	0.2645

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.065801	.0176318	3.73	0.000	.0312434	.1003586
radhlw1	.004144	.0061988	0.67	0.504	-.0080054	.0162935
bf1	.0313968	.0422548	0.74	0.457	-.051421	.1142146
bf20	-.0193584	.0374978	-0.52	0.606	-.0928527	.0541359
deawl	-.5581614	.4525925	-1.23	0.217	-1.445226	.3289037
shhlw1	.0137667	.0070908	1.94	0.052	-.000131	.0276644
shjobw1	.0236604	.0075625	3.13	0.002	.0088381	.0384826
shrelaw1	-.0149185	.006252	-2.39	0.017	-.0271722	-.0026648
suprtw1	.0010509	.0069016	0.15	0.879	-.012476	.0145778
_cons	-7.048599	1.70409	-4.14	0.000	-10.38855	-3.708644

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	13	0	13
-	28	299	327
Total	41	299	340

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	31.71%
Specificity	$\Pr(- \sim D)$	100.00%
Positive predictive value	$\Pr(D +)$	100.00%
Negative predictive value	$\Pr(\sim D -)$	91.44%

False + rate for true ~D	$\Pr(+ \sim D)$	0.00%
False - rate for true D	$\Pr(- D)$	68.29%
False + rate for classified +	$\Pr(\sim D +)$	0.00%
False - rate for classified -	$\Pr(D -)$	8.56%

Correctly classified	91.76%
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Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	340
number of covariate patterns =	333
Pearson $\chi^2(323)$ =	450.80
Prob > χ^2 =	0.0000

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-92.052
D(330):	184.103	LR(9):	66.202
		Prob > LR:	0.000
McFadden's R2:	0.264	McFadden's Adj R2:	0.185
Maximum Likelihood R2:	0.177	Cragg & Uhler's R2:	0.340
McKelvey and Zavoina's R2:	0.458	Efron's R2:	0.278
Variance of y*:	6.073	Variance of error:	3.290
Count R2:	0.918	Adj Count R2:	0.317
AIC:	0.600	AIC*n:	204.103
BIC:	-1739.449	BIC':	-13.741

Full main model for HP2probsoc for wave= 1

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

Full Nottingham Part 2 HP2probsoc subscale models

Logistic regression	Number of obs	=	361
	LR chi2(9)	=	102.23
	Prob > chi2	=	0.0000
Log likelihood = -131.99945	Pseudo R2	=	0.2791

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1172627	.0171673	6.83	0.000	.0836153	.1509101
radhlw1	.0111397	.0049416	2.25	0.024	.0014543	.0208251
bf1	.0362951	.0284738	1.27	0.202	-.0195124	.0921027
bf20	-.0253268	.0231741	-1.09	0.274	-.0707472	.0200936
deaw1	-.0870921	.1767587	-0.49	0.622	-.4335327	.2593485
shhlw1	.0025727	.0062142	0.41	0.679	-.009607	.0147524
shjobw1	.0087888	.0058839	1.49	0.135	-.0027435	.020321
shrelaw1	-.0093887	.0051896	-1.81	0.070	-.0195601	.0007827
suprtw1	.0013382	.0045531	0.29	0.769	-.0075856	.0102621
_cons	-8.243948	1.264801	-6.52	0.000	-10.72291	-5.764984

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	33	14	47
-	41	273	314
Total	74	287	361

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

Sensitivity	$\Pr(+ D)$	44.59%
Specificity	$\Pr(- \sim D)$	95.12%
Positive predictive value	$\Pr(D +)$	70.21%
Negative predictive value	$\Pr(\sim D -)$	86.94%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	4.88%
False - rate for true D	$\Pr(- D)$	55.41%
False + rate for classified +	$\Pr(\sim D +)$	29.79%
False - rate for classified -	$\Pr(D -)$	13.06%

Correctly classified		84.76%
----------------------	--	---------------

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	361
number of covariate patterns =	359
Pearson $\chi^2(349)$ =	399.18
Prob > χ^2 =	0.0329

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-183.113	Log-Lik Full Model:	-131.999
D(351):	263.999	LR(9):	102.227
		Prob > LR:	0.000
McFadden's R2:	0.279	McFadden's Adj R2:	0.225
Maximum Likelihood R2:	0.247	Cragg & Uhler's R2:	0.387
McKelvey and Zavoina's R2:	0.459	Efron's R2:	0.306
Variance of y*:	6.086	Variance of error:	3.290
Count R2:	0.848	Adj Count R2:	0.257
AIC:	0.787	AIC*n:	283.999
BIC:	-1802.997	BIC':	-49.227

Full main model for HP2pbfhm for wave= 1

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

Full Nottingham Part 2 HP2pbfhm subscale models

Logistic regression

Number of obs = 340

LR chi2(9) = 22.29

Prob > chi2 = 0.0080

Log likelihood = -70.363535

Pseudo R2 = 0.1367

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0531285	.0215313	2.47	0.014	.0109279	.0953291
radhlw1	.0202681	.008252	2.46	0.014	.0040946	.0364417
bf1	-.0087893	.0546645	-0.16	0.872	-.1159298	.0983511
bf20	.007857	.0497616	0.16	0.875	-.0896739	.1053879
deawl	-.0860305	.4565197	-0.19	0.851	-.9807926	.8087316
shhlw1	.005778	.0099994	0.58	0.563	-.0138205	.0253765
shjobw1	-.0120291	.0099428	-1.21	0.226	-.0315167	.0074584
shrelaw1	.0007624	.0073877	0.10	0.918	-.0137173	.015242
suprtw1	-.018106	.0125821	-1.44	0.150	-.0427664	.0065544
_cons	-6.445038	2.186355	-2.95	0.003	-10.73022	-2.159861

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%

Logistic model for HP2pbfhm, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      333
      Pearson chi2(323) =      349.26
      Prob > chi2 =      0.1510

```

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-81.506	Log-Lik Full Model:	-70.364
D(330):	140.727	LR(9):	22.285
		Prob > LR:	0.008
McFadden's R2:	0.137	McFadden's Adj R2:	0.014
Maximum Likelihood R2:	0.063	Cragg & Uhler's R2:	0.167
McKelvey and Zavoina's R2:	0.285	Efron's R2:	0.087
Variance of y*:	4.600	Variance of error:	3.290
Count R2:	0.935	Adj Count R2:	0.000
AIC:	0.473	AIC*n:	160.727
BIC:	-1782.825	BIC':	30.175

Full main model for HP2pbfhm for wave= 1

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

Full Nottingham Part 2 HP2pbfhm subscale models

Logistic regression	Number of obs	=	361
	LR chi2(9)	=	54.48
	Prob > chi2	=	0.0000
Log likelihood = -112.37659	Pseudo R2	=	0.1951

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0764706	.0168625	4.53	0.000	.0434207	.1095204
radhlw1	.0197767	.0060446	3.27	0.001	.0079295	.0316239
bf1	.0102198	.0319073	0.32	0.749	-.0523175	.072757
bf20	-.0098859	.0262026	-0.38	0.706	-.0612421	.0414703
deawl	-.1694401	.2100502	-0.81	0.420	-.5811308	.2422507
shhlw1	.0028786	.0067993	0.42	0.672	-.0104478	.0162051
shjobw1	.0109885	.0066829	1.64	0.100	-.0021097	.0240866
shrelaw1	-.0061099	.0055939	-1.09	0.275	-.0170736	.0048539
suprtw1	-.0018698	.0055191	-0.34	0.735	-.012687	.0089474
_cons	-7.471036	1.391934	-5.37	0.000	-10.19918	-4.742896

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	9	3	12
-	38	311	349
Total	47	314	361

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	19.15%
Specificity	$\Pr(- \sim D)$	99.04%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	89.11%

False + rate for true ~D	$\Pr(+ \sim D)$	0.96%
False - rate for true D	$\Pr(- D)$	80.85%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	10.89%

Correctly classified	88.64%
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Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	361
number of covariate patterns =	359
Pearson chi2(349) =	423.47
Prob > chi2 =	0.0039

Measures of Fit for **logit** of HP2pbfhm

Log-Lik Intercept Only:	-139.619	Log-Lik Full Model:	-112.377
D(351):	224.753	LR(9):	54.484
		Prob > LR:	0.000
McFadden's R2:	0.195	McFadden's Adj R2:	0.123
Maximum Likelihood R2:	0.140	Cragg & Uhler's R2:	0.260
McKelvey and Zavoina's R2:	0.363	Efron's R2:	0.208
Variance of y*:	5.164	Variance of error:	3.290
Count R2:	0.886	Adj Count R2:	0.128
AIC:	0.678	AIC*n:	244.753
BIC:	-1842.243	BIC':	-1.484

Full main model for HP2sxlife for wave= 1

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

Full Nottingham Part 2 HP2sxlife subscale models

Logistic regression	Number of obs	=	340
	LR chi2(9)	=	85.53
	Prob > chi2	=	0.0000
Log likelihood = -128.75122	Pseudo R2	=	0.2493

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0794939	.014719	5.40	0.000	.0506451	.1083426
radhlw1	.009177	.0050435	1.82	0.069	-.000708	.019062
bf1	.0255037	.0309771	0.82	0.410	-.0352102	.0862176
bf20	-.0168051	.0267683	-0.63	0.530	-.0692699	.0356598
deaw1	.3968761	.2712323	1.46	0.143	-.1347295	.9284817
shhlw1	.0053833	.0061644	0.87	0.383	-.0066986	.0174652
shjobw1	.0120161	.0057139	2.10	0.035	.0008171	.0232151
shrelaw1	-.0034493	.0049958	-0.69	0.490	-.0132409	.0063423
suprtw1	-.001828	.0055711	-0.33	0.743	-.0127471	.0090912
_cons	-6.639149	1.272534	-5.22	0.000	-9.133269	-4.145029

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	26	16	42
-	43	255	298
Total	69	271	340

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

Sensitivity	$\Pr(+ D)$	37.68%
Specificity	$\Pr(- \sim D)$	94.10%
Positive predictive value	$\Pr(D +)$	61.90%
Negative predictive value	$\Pr(\sim D -)$	85.57%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.90%
False - rate for true D	$\Pr(- D)$	62.32%
False + rate for classified +	$\Pr(\sim D +)$	38.10%
False - rate for classified -	$\Pr(D -)$	14.43%

Correctly classified		82.65%
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Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	340
number of covariate patterns =	333
Pearson $\chi^2(323)$ =	317.29
Prob > χ^2 =	0.5792

Measures of Fit for **logit** of HP2sxlife

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-128.751
D(330):	257.502	LR(9):	85.525
		Prob > LR:	0.000
McFadden's R2:	0.249	McFadden's Adj R2:	0.191
Maximum Likelihood R2:	0.222	Cragg & Uhler's R2:	0.350
McKelvey and Zavoina's R2:	0.413	Efron's R2:	0.252
Variance of y^* :	5.605	Variance of error:	3.290
Count R2:	0.826	Adj Count R2:	0.145
AIC:	0.816	AIC*n:	277.502
BIC:	-1666.050	BIC':	-33.065

Full main model for HP2sxlife for wave= 1

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

Full Nottingham Part 2 HP2sxlife subscale models

Logistic regression

Number of obs = 361

LR chi2(9) = 98.58

Prob > chi2 = 0.0000

Pseudo R2 = 0.2381

Log likelihood = -157.72791

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0955211	.0143598	6.65	0.000	.0673765	.1236658
radhlw1	.0076884	.0043462	1.77	0.077	-.00083	.0162068
bf1	.0126394	.0277031	0.46	0.648	-.0416577	.0669365
bf20	-.0012302	.0235195	-0.05	0.958	-.0473276	.0448672
deawl	.0002926	.1487155	0.00	0.998	-.2911845	.2917697
shhlw1	-.0067303	.0056634	-1.19	0.235	-.0178304	.0043698
shjobw1	.0163073	.0053284	3.06	0.002	.0058638	.0267508
shrelaw1	-.0028221	.0044927	-0.63	0.530	-.0116277	.0059835
suprtw1	.001642	.0041364	0.40	0.691	-.0064651	.0097491
_cons	-7.57151	1.189708	-6.36	0.000	-9.903294	-5.239726

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	41	20	61
-	53	247	300
Total	94	267	361

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	43.62%
Specificity	$\Pr(- \sim D)$	92.51%
Positive predictive value	$\Pr(D +)$	67.21%
Negative predictive value	$\Pr(\sim D -)$	82.33%
False + rate for true ~D	$\Pr(+ \sim D)$	7.49%
False - rate for true D	$\Pr(- D)$	56.38%
False + rate for classified +	$\Pr(\sim D +)$	32.79%
False - rate for classified -	$\Pr(D -)$	17.67%
Correctly classified		79.78%

Logistic model for HP2sxlife, goodness-of-fit test

```

      number of observations =      361
number of covariate patterns =      359
      Pearson chi2(349) =      354.34
      Prob > chi2 =      0.4105

```

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

Log-Lik Intercept Only:	-207.020	Log-Lik Full Model:	-157.728
D(351):	315.456	LR(9):	98.584
		Prob > LR:	0.000
McFadden's R2:	0.238	McFadden's Adj R2:	0.190
Maximum Likelihood R2:	0.239	Cragg & Uhler's R2:	0.350
McKelvey and Zavoina's R2:	0.392	Efron's R2:	0.265
Variance of y*:	5.408	Variance of error:	3.290
Count R2:	0.798	Adj Count R2:	0.223
AIC:	0.929	AIC*n:	335.456
BIC:	-1751.540	BIC':	-45.584

Full main model for HP2inthob for wave= 1

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

Full Nottingham Part 2 HP2inthob subscale models

Logistic regression	Number of obs	=	340
	LR chi2(9)	=	62.70
	Prob > chi2	=	0.0000
Log likelihood = -87.714325	Pseudo R2	=	0.2633

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0469277	.0177122	2.65	0.008	.0122124	.0816431
radhlw1	.0188772	.0066787	2.83	0.005	.0057871	.0319672
bf1	-1.367019	102.0878	-0.01	0.989	-201.4554	198.7214
bf20	1.370719	102.0878	0.01	0.989	-198.7177	201.4591
deawl	-1.420629	.7247073	-1.96	0.050	-2.841029	-.000229
shhlw1	.0101692	.007213	1.41	0.159	-.0039681	.0243065
shjobw1	.0095172	.0070594	1.35	0.178	-.0043189	.0233533
shrelaw1	-.0074121	.00618	-1.20	0.230	-.0195247	.0047004
suprtw1	.0120175	.0067365	1.78	0.074	-.0011857	.0252207
_cons	-61.4171	4083.511	-0.02	0.988	-8064.952	7942.118

Note: 23 failures and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	8	1	9
-	30	301	331
Total	38	302	340

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	21.05%
Specificity	$\Pr(- \sim D)$	99.67%
Positive predictive value	$\Pr(D +)$	88.89%
Negative predictive value	$\Pr(\sim D -)$	90.94%
False + rate for true ~D	$\Pr(+ \sim D)$	0.33%
False - rate for true D	$\Pr(- D)$	78.95%
False + rate for classified +	$\Pr(\sim D +)$	11.11%
False - rate for classified -	$\Pr(D -)$	9.06%
Correctly classified		90.88%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	340
number of covariate patterns =	333
Pearson chi2(323) =	332.44
Prob > chi2 =	0.3467

Measures of Fit for **logit** of HP2inthob

Log-Lik Intercept Only:	-119.064	Log-Lik Full Model:	-87.714
D(330):	175.429	LR(9):	62.700
		Prob > LR:	0.000
McFadden's R2:	0.263	McFadden's Adj R2:	0.179
Maximum Likelihood R2:	0.168	Cragg & Uhler's R2:	0.334
McKelvey and Zavoina's R2:	0.965	Efron's R2:	0.239
Variance of y*:	94.491	Variance of error:	3.290
Count R2:	0.909	Adj Count R2:	0.184
AIC:	0.575	AIC*n:	195.429
BIC:	-1748.123	BIC':	-10.239

Full main model for HP2inthob for wave= 1

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

Full Nottingham Part 2 HP2inthob subscale models

Logistic regression	Number of obs	=	361
	LR chi2(9)	=	79.74
	Prob > chi2	=	0.0000
Log likelihood = -131.84212	Pseudo R2	=	0.2322

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0887071	.0158463	5.60	0.000	.0576489	.1197652
radhlw1	.0197231	.0053656	3.68	0.000	.0092067	.0302394
bf1	-.033217	.0371955	-0.89	0.372	-.1061189	.0396848
bf20	.0312708	.0332387	0.94	0.347	-.0338758	.0964173
deawl	-.01341	.1602451	-0.08	0.933	-.3274847	.3006646
shhlw1	.0056196	.006261	0.90	0.369	-.0066516	.0178909
shjobw1	.0023075	.0060411	0.38	0.702	-.0095328	.0141479
shrelaw1	-.0033791	.0049976	-0.68	0.499	-.0131743	.0064161
suprtw1	.0018167	.0046916	0.39	0.699	-.0073787	.011012
_cons	-9.026372	1.602951	-5.63	0.000	-12.1681	-5.884647

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	26	6	32
-	40	289	329
Total	66	295	361

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	39.39%
Specificity	$\Pr(- \sim D)$	97.97%
Positive predictive value	$\Pr(D +)$	81.25%
Negative predictive value	$\Pr(\sim D -)$	87.84%
False + rate for true ~D	$\Pr(+ \sim D)$	2.03%
False - rate for true D	$\Pr(- D)$	60.61%
False + rate for classified +	$\Pr(\sim D +)$	18.75%
False - rate for classified -	$\Pr(D -)$	12.16%
Correctly classified		87.26%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      361
number of covariate patterns =    359
    Pearson chi2(349) =    429.70
        Prob > chi2 =      0.0020

```

Measures of Fit for **logit** of HP2inthob

Log-Lik Intercept Only:	-171.710	Log-Lik Full Model:	-131.842
D(351):	263.684	LR(9):	79.736
		Prob > LR:	0.000
McFadden's R2:	0.232	McFadden's Adj R2:	0.174
Maximum Likelihood R2:	0.198	Cragg & Uhler's R2:	0.323
McKelvey and Zavoina's R2:	0.408	Efron's R2:	0.269
Variance of y*:	5.559	Variance of error:	3.290
Count R2:	0.873	Adj Count R2:	0.303
AIC:	0.786	AIC*n:	283.684
BIC:	-1803.312	BIC':	-26.736

Full main model for HP2vacatn for wave= 1

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

Full Nottingham Part 2 HP2vacatn subscale models

Logistic regression	Number of obs	=	340
	LR chi2(9)	=	63.50
	Prob > chi2	=	0.0000
Log likelihood = -93.400079	Pseudo R2	=	0.2537

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0680461	.0174883	3.89	0.000	.0337697	.1023225
radhlw1	.0124707	.0061517	2.03	0.043	.0004136	.0245278
bf1	-.0963654	.0889765	-1.08	0.279	-.2707562	.0780254
bf20	.0856524	.0861894	0.99	0.320	-.0832757	.2545804
deawl	-1.062962	.5930123	-1.79	0.073	-2.225245	.0993207
shhlw1	.0106702	.0069711	1.53	0.126	-.0029929	.0243333
shjobw1	.0181404	.0071032	2.55	0.011	.0042184	.0320624
shrelaw1	-.0112469	.0061227	-1.84	0.066	-.0232473	.0007534
suprtw1	.0083536	.0065604	1.27	0.203	-.0045047	.0212118
_cons	-10.52227	3.506457	-3.00	0.003	-17.3948	-3.649741

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	8	4	12
-	33	295	328
Total	41	299	340

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

Sensitivity	$\Pr(+ D)$	19.51%
Specificity	$\Pr(- \sim D)$	98.66%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	89.94%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.34%
False - rate for true D	$\Pr(- D)$	80.49%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	10.06%

Correctly classified	89.12%
----------------------	---------------

Logistic model for HP2vacatn, goodness-of-fit test

number of observations =	340
number of covariate patterns =	333
Pearson $\chi^2(323)$ =	324.00
Prob > χ^2 =	0.4740

Measures of Fit for **logit** of HP2vacatn

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-93.400
D(330):	186.800	LR(9):	63.505
		Prob > LR:	0.000
McFadden's R2:	0.254	McFadden's Adj R2:	0.174
Maximum Likelihood R2:	0.170	Cragg & Uhler's R2:	0.327
McKelvey and Zavoina's R2:	0.472	Efron's R2:	0.242
Variance of y*:	6.227	Variance of error:	3.290
Count R2:	0.891	Adj Count R2:	0.098
AIC:	0.608	AIC*n:	206.800
BIC:	-1736.752	BIC':	-11.044

Full main model for HP2vacatn for wave= 1

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

Full Nottingham Part 2 HP2vacatn subscale models

Logistic regression

Number of obs = 361

LR chi2(9) = 82.63

Prob > chi2 = 0.0000

Pseudo R2 = 0.2472

Log likelihood = -125.82087

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0884841	.0163538	5.41	0.000	.0564313	.1205368
radhlw1	.0261977	.0057913	4.52	0.000	.014847	.0375484
bf1	-.0344464	.0312123	-1.10	0.270	-.0956214	.0267286
bf20	.0183328	.0265608	0.69	0.490	-.0337255	.070391
deawl	-.0152546	.1698279	-0.09	0.928	-.3481113	.317602
shhlw1	-.0000247	.0063261	-0.00	0.997	-.0124237	.0123742
shjobw1	.0075507	.0061271	1.23	0.218	-.0044583	.0195596
shrelaw1	-.0045753	.0052069	-0.88	0.380	-.0147807	.0056301
suprtw1	.0082219	.0046149	1.78	0.075	-.0008231	.017267
_cons	-8.575778	1.434965	-5.98	0.000	-11.38826	-5.763298

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	23	6	29
-	40	292	332
Total	63	298	361

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

True D defined as HP2vacatn != 0

Sensitivity	$\Pr(+ D)$	36.51%
Specificity	$\Pr(- \sim D)$	97.99%
Positive predictive value	$\Pr(D +)$	79.31%
Negative predictive value	$\Pr(\sim D -)$	87.95%
False + rate for true ~D	$\Pr(+ \sim D)$	2.01%
False - rate for true D	$\Pr(- D)$	63.49%
False + rate for classified +	$\Pr(\sim D +)$	20.69%
False - rate for classified -	$\Pr(D -)$	12.05%
Correctly classified		87.26%

Logistic model for HP2vacatn, goodness-of-fit test

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

```
120 .
121 . set more off

122 . *-----Chunk 2 dosew1 moderator paid employment impact-----
    > ----
123 . title "1.  H1 pt2 wv 2 male cum rad dose wrt HP2work impact "
```



```

124 . * male models
125 .       forvalues j=1/1 {
      2.         set more off
      3. title4 "trimmed HP2work main effects models wave 1 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 1 for H1 part 2 with dose ns

Wave 1 dose HP2work relationship but avgcumdosew1: Dose not signif

Gender =1 HP2work model

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -145.38341
Iteration 2:  log likelihood = -143.32275
Iteration 3:  log likelihood = -143.31043
Iteration 4:  log likelihood = -143.31043

```

Logistic regression	Number of obs	=	340
	LR chi2(8)	=	59.12
	Prob > chi2	=	0.0000
Log likelihood = -143.31043	Pseudo R2	=	0.1710

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0048446	.0141529	0.34	0.732	-.0228945	.0325838
bf4	-.1400119	.0321951	-4.35	0.000	-.2031132	-.0769107
bf40	.3309236	.0941317	3.52	0.000	.1464287	.5154184
illw1	-.2284418	.3531212	-0.65	0.518	-.9205467	.4636631
movew1	.4467728	.4500499	0.99	0.321	-.4353089	1.328854
shrelaw1	.0013722	.0039941	0.34	0.731	-.0064562	.0092005
avgcumdosew1	.014672	.0771675	0.19	0.849	-.1365736	.1659175
radhlw1	-.0007224	.0043698	-0.17	0.869	-.009287	.0078422
_cons	-.8602236	.9469206	-0.91	0.364	-2.716154	.9957067

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	17	15	32
-	53	255	308
Total	70	270	340

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

Sensitivity	$\Pr(+ D)$	24.29%
Specificity	$\Pr(- \sim D)$	94.44%
Positive predictive value	$\Pr(D +)$	53.12%
Negative predictive value	$\Pr(\sim D -)$	82.79%
False + rate for true ~D	$\Pr(+ \sim D)$	5.56%
False - rate for true D	$\Pr(- D)$	75.71%
False + rate for classified +	$\Pr(\sim D +)$	46.88%
False - rate for classified -	$\Pr(D -)$	17.21%
Correctly classified		80.00%

Logistic model for HP2work, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      335
      Pearson chi2(326) =      303.46
              Prob > chi2 =      0.8099
  
```

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

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-143.310
D(331):	286.621	LR(8):	59.125
		Prob > LR:	0.000
McFadden's R2:	0.171	McFadden's Adj R2:	0.119
Maximum Likelihood R2:	0.160	Cragg & Uhler's R2:	0.250
McKelvey and Zavoina's R2:	0.254	Efron's R2:	0.166
Variance of y*:	4.413	Variance of error:	3.290
Count R2:	0.800	Adj Count R2:	0.029
AIC:	0.896	AIC*n:	304.621
BIC:	-1642.760	BIC':	-12.493

```

126 .
127 . title4 "Constructing male moderators of HP2work in wave 1"

```

```

Constructing male moderators of HP2work in wave 1

```

```

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

131 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd1 = `var'*avgcumdosew1
      3. label var `var'Xd1 "interaction of avgcumdosew1 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=1/1 {
      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 1

```

```

title2: Wave `j' dose HP2work relationship but avgcumdosew1: Dose not signif
Date and time: 18 Jun 2012 18:11:05
Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/hltests/hlpt2
Stata data file: chwide16june2012.dta
> has 2369 variables and 703 observations

```

```

Wave `j' dose HP2work relationship but avgcumdosew1: Dose not signif

```

```

138 .
139 .
140 . set more off

141 .
142 . forvalues j=1/1 {
      2.          sw, pr(.1):logistic HP2work age bf4 bf40 movew`j' shrelaw
> `j'  ///
>          avgcumdosew`j' illw1 radhlw`j' bf4Xd1 bf40Xd1 if gender==1,
> coef
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.8072 >= 0.1000 removing avgcumdosew1
p = 0.7761 >= 0.1000 removing shrelaw1
p = 0.7348 >= 0.1000 removing age
p = 0.7348 >= 0.1000 removing radhlw1
p = 0.3215 >= 0.1000 removing movew1
p = 0.2131 >= 0.1000 removing illw1
p = 0.2607 >= 0.1000 removing bf40Xd1
p = 0.9419 >= 0.1000 removing bf4Xd1

```

```

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

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	18	14	32
-	52	256	308
Total	70	270	340

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

Sensitivity	$\Pr(+ D)$	25.71%
Specificity	$\Pr(- \sim D)$	94.81%
Positive predictive value	$\Pr(D +)$	56.25%
Negative predictive value	$\Pr(\sim D -)$	83.12%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.19%
False - rate for true D	$\Pr(- D)$	74.29%
False + rate for classified +	$\Pr(\sim D +)$	43.75%
False - rate for classified -	$\Pr(D -)$	16.88%
Correctly classified		80.59%

Logistic model for HP2work, goodness-of-fit test

number of observations =	340
number of covariate patterns =	91
Pearson $\chi^2(88)$ =	104.61
Prob > χ^2 =	0.1092

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

```

143 .
144 . logit hp2work bf4 bf40 avgcumdosew1 radhlw1 havmilsq if gender==1

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -146.04951
Iteration 2:  log likelihood = -144.07501
Iteration 3:  log likelihood = -144.06434
Iteration 4:  log likelihood = -144.06434

```

```

Logistic regression                                Number of obs   =       340
                                                    LR chi2(5)      =       57.62
                                                    Prob > chi2     =       0.0000
Log likelihood = -144.06434                      Pseudo R2      =       0.1666

```

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1443876	.0307305	-4.70	0.000	-.2046181	-.084157
bf40	.3278933	.0856676	3.83	0.000	.1599879	.4957988
avgcumdosew1	.0103223	.0782446	0.13	0.895	-.1430344	.1636789
radhlw1	-.00017	.0043575	-0.04	0.969	-.0087106	.0083705
havamilsq	-5.54e-08	1.66e-06	-0.03	0.973	-3.32e-06	3.21e-06
_cons	-.5281323	.5641161	-0.94	0.349	-1.63378	.577515

```

145 . logit hp2work bf4 bf40 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]	
bf4	-.1439508	.0277538	-5.19	0.000	-.1983472	-.0895544
bf40	.3278445	.0853217	3.84	0.000	.160617	.495072
_cons	-.5378471	.4253878	-1.26	0.206	-1.371592	.2958977

146 . estat class

Logistic model for hp2work

Classified	True		Total
	D	~D	
+	18	14	32
-	52	256	308
Total	70	270	340

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

True D defined as hp2work != 0

Sensitivity	$\Pr(+ D)$	25.71%
Specificity	$\Pr(- \sim D)$	94.81%
Positive predictive value	$\Pr(D +)$	56.25%
Negative predictive value	$\Pr(\sim D -)$	83.12%
False + rate for true ~D	$\Pr(+ \sim D)$	5.19%
False - rate for true D	$\Pr(- D)$	74.29%
False + rate for classified +	$\Pr(\sim D +)$	43.75%
False - rate for classified -	$\Pr(D -)$	16.88%
Correctly classified		80.59%

147 . estat gof

Logistic model for hp2work, goodness-of-fit test

number of observations =	340
number of covariate patterns =	91
Pearson $\chi^2(88)$ =	104.61
Prob > χ^2 =	0.1092

148 . fitstat

Measures of Fit for **logit** 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

149 .

150 . * capturing significant vars from last analysis

151 . local cn1: colnames(e(b))

152 . di "`cn1'"

bf4 bf40 _cons

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

154 . di `leng1'

14

155 . local leng1b `leng1'-6

156 . di `leng1b'

8

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

158 . di "`nuvlist'"

bf4 bf40

```
159 . local rhsvars = "`nuvlist'"
```

```
160 . local nuvlist= "`nuvlist'"
```

```
161 . local nuvlist= substr("`cn1'",1,`lengthb')
```

```
162 . di "`nuvlist'"
```

```
bf4 bf40
```

```
163 . sw, pr(.1):logit hp2hmcare `nuvlist' if gender==1
```

```
begin with full model
```

```
p < 0.1000 for all terms in model
```

```
Logistic regression
```

```
Number of obs = 340
```

```
LR chi2(2) = 81.32
```

```
Prob > chi2 = 0.0000
```

```
Pseudo R2 = 0.2352
```

```
Log likelihood = -132.21538
```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.2248287	.0309809	-7.26	0.000	-.2855501	-.1641072
bf40	.1658314	.0893229	1.86	0.063	-.0092382	.340901
_cons	.7314062	.4552436	1.61	0.108	-.1608548	1.623667

```
164 . di "`rhsvars'"
```

```
bf4 bf40
```

```
165 . matrix define c=e(b)
```

```
166 . local cn2: colnames(c)
```

```
167 . di "`cn2'"
```

```
bf4 bf40 _cons
```

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

```

169 . local leng2b = `leng2'-6
170 . local rhsvars = substr("`cn2'",1,`leng2b')
171 . 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]	
bf4	-.1439508	.0277538	-5.19	0.000	-.1983472	-.0895544
bf40	.3278445	.0853217	3.84	0.000	.160617	.495072
_cons	-.5378471	.4253878	-1.26	0.206	-1.371592	.2958977

```

172 .
173 .
174 .
175 . di "`rhsvars'"
    bf4 bf40
176 . local varlist2 =substr("`rhsvars'",1,9)
177 . di "`varlist2'"
    bf4 bf40
178 .

```

```

179 . * constructing potential moderators
180 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd1 = `var'* avgcumdosew1
      3. }

181 .
182 . *x no signif male moderators for paid employment
183 . set more off

184 . sw, pr(.1): logistic hp2work `rhsvars' bf4Xd1 bf40Xd1 if gender==1, coef
      begin with full model
p = 0.2607 >= 0.1000 removing bf40Xd1
p = 0.9419 >= 0.1000 removing bf4Xd1

```

```

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]	
bf4	-.1439508	.0277538	-5.19	0.000	-.1983472	-.0895544
bf40	.3278445	.0853217	3.84	0.000	.160617	.495072
_cons	-.5378471	.4253878	-1.26	0.206	-1.371592	.2958977

```
185 . 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

```

```

186 .
187 . scalar wkModMw1 = "none"

188 . di _skip(2)

189 . title4 "testing the female moderator model Hp2work H1 Pt 2 wave 1"
      _____
      testing the female moderator model Hp2work H1 Pt 2 wave 1
      _____

190 . * Testing female moderator model xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      > xxxxx
191 .
192 . title4 "testing general female moderator model for hp2work"
      _____
      testing general female moderator model for hp2work
      _____

193 . local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40

194 . di _skip(4)

195 .
196 .
197 . forvalues j=1/1 {
      2. set more off
      3. di _skip(4)
      4. di as input "For females hp2work on wave 1 with dose ns"
      5. des age occ1w`j'-occ8w`j' inc1w`j'-inc4w`j' avgcumdosew`j' `w1bf'
      6. sw, pr(.1): logistic HP2work age havmilsq ///
      > avgcumdosew1 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 1 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w1	double	%15.0g	LABJ	profess executive administration in 1986
occ2w1	double	%15.0g	LABJ	technical sales admin support in 1986
occ3w1	double	%15.0g	LABJ	service occup protective services in 1986
occ4w1	double	%15.0g	LABJ	precision prod mechan craft construction in 1986
occ5w1	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1986
occ6w1	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1986
occ7w1	double	%15.0g	LABJ	homemaking or caregiving in 1986
occ8w1	double	%15.0g	LABJ	student in 1986
inc1w1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
avgcumdosew1	double	%8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986
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)
bf10	float	%9.0g		bf10= max(0, sufamw1 - 20)
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
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

begin with full model

p = **0.9219** >= 0.1000 removing **suprtw1**
p = **0.8867** >= 0.1000 removing **shjobw1**
p = **0.6189** >= 0.1000 removing **havmilsq**
p = **0.1241** >= 0.1000 removing **avgcumdosew1**

Logistic regression

Number of obs = 361

LR chi2(3) = 46.25

Prob > chi2 = 0.0000

Log likelihood = -182.84519

Pseudo R2 = 0.1123

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0626548	.0119743	5.23	0.000	.0391855	.086124
radhlw1	.0071024	.0037129	1.91	0.056	-.0001748	.0143795
illw1	.4077261	.2382216	1.71	0.087	-.0591797	.8746319
_cons	-4.859841	.6646145	-7.31	0.000	-6.162461	-3.55722

Logistic model for HP2work, goodness-of-fit test

number of observations = 361
 number of covariate patterns = 253
 Pearson chi2(249) = 271.11
 Prob > chi2 = 0.1605

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	24	6	30
-	69	262	331
Total	93	268	361

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	25.81%
Specificity	$\Pr(- \sim D)$	97.76%
Positive predictive value	$\Pr(D +)$	80.00%
Negative predictive value	$\Pr(\sim D -)$	79.15%

False + rate for true ~D	$\Pr(+ \sim D)$	2.24%
False - rate for true D	$\Pr(- D)$	74.19%
False + rate for classified +	$\Pr(\sim D +)$	20.00%
False - rate for classified -	$\Pr(D -)$	20.85%

Correctly classified	79.22%
----------------------	--------

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

Log-Lik Intercept Only:	-205.969	Log-Lik Full Model:	-182.845
D(357):	365.690	LR(3):	46.247
		Prob > LR:	0.000
McFadden's R2:	0.112	McFadden's Adj R2:	0.093
Maximum Likelihood R2:	0.120	Cragg & Uhler's R2:	0.177
McKelvey and Zavoina's R2:	0.192	Efron's R2:	0.141
Variance of y*:	4.072	Variance of error:	3.290
Count R2:	0.792	Adj Count R2:	0.194
AIC:	1.035	AIC*n:	373.690
BIC:	-1736.639	BIC':	-28.580

```

198 .
199 . cap gen ageXd1 = age*avgcumdosew1

200 .
201 . * capturing significant vars
202 . local cn3: colnames(e(b))

203 . di "`cn3'"
    age radhlw1 illw1 _cons

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

205 . di `leng3'
    23

206 . local leng3b `leng3'-6

207 . di `leng3b'
    17

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

209 . di "`nuvlist3'"
    age radhlw1 illw1

```

```

210 . local rhsvars3 = "`nuvlist3'"
211 . local rhsvars4= substr("`cn3'",1,`leng3b')
212 . di "`rhsvars4'"
    age radhlw1 illw1
213 .
214 . * moderators for hp2work female and male are saved as scalars:
215 . scalar wkModFw1="none"
216 . scalar wkModMw1="none"
217 . cap gen ageXd1 = age*avgcumdosew1
218 .
219 . *x no significant female moderator for paid employment
220 . forvalues j=1/1 {
    2. di as input "For females hp2probsoc on wave 1 with dose ns"
    3. des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j'
    4. set more off
    5. sw, pr(.1): logistic HP2work bf4 bf14 age havmil ///
>   avgcumdosew1 ageXd1 illw`j' accdw`j' suprtw`j' if gender==2, coef
    6. estat gof
    7. estat class
    8. fitstat
    9. }
For females hp2probsoc on wave 1 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w1	double	%15.0g	LABJ	profess executive administration in 1986
occ2w1	double	%15.0g	LABJ	technical sales admin support in 1986
occ3w1	double	%15.0g	LABJ	service occup protective services in 1986
occ4w1	double	%15.0g	LABJ	precision prod mechan craft construction in 1986
occ5w1	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1986
occ6w1	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1986
occ7w1	double	%15.0g	LABJ	homemaking or caregiving in 1986
occ8w1	double	%15.0g	LABJ	student in 1986
incl1w1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986

inc2w1	double %15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double %15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double %15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
avgcumdosew1	double %8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986

```

begin with full model
p = 0.9043 >= 0.1000 removing suprtw1
p = 0.5398 >= 0.1000 removing accdw1
p = 0.4992 >= 0.1000 removing havmil
p = 0.3576 >= 0.1000 removing illw1
p = 0.2119 >= 0.1000 removing ageXd1
p = 0.1822 >= 0.1000 removing avgcumdosew1
p = 0.2326 >= 0.1000 removing bf14

```

Logistic regression	Number of obs	=	362
	LR chi2(2)	=	59.51
	Prob > chi2	=	0.0000
Log likelihood = -176.51284	Pseudo R2	=	0.1442

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1117282	.0265443	-4.21	0.000	-.163754	-.0597024
age	.0511864	.01239	4.13	0.000	.0269024	.0754704
_cons	-2.684594	.7848001	-3.42	0.001	-4.222774	-1.146414

Logistic model for HP2work, goodness-of-fit test

```

number of observations = 362
number of covariate patterns = 274
Pearson chi2(271) = 303.76
Prob > chi2 = 0.0834

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	31	18	49
-	62	251	313
Total	93	269	362

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

Sensitivity	$\Pr(+ D)$	33.33%
Specificity	$\Pr(- \sim D)$	93.31%
Positive predictive value	$\Pr(D +)$	63.27%
Negative predictive value	$\Pr(\sim D -)$	80.19%

False + rate for true $\sim D$	$\Pr(+ \sim D)$	6.69%
False - rate for true D	$\Pr(- D)$	66.67%
False + rate for classified +	$\Pr(\sim D +)$	36.73%
False - rate for classified -	$\Pr(D -)$	19.81%

Correctly classified		77.90%
----------------------	--	---------------

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

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-176.513
D(359):	353.026	LR(2):	59.506
		Prob > LR:	0.000
McFadden's R2:	0.144	McFadden's Adj R2:	0.130
Maximum Likelihood R2:	0.152	Cragg & Uhler's R2:	0.223
McKelvey and Zavoina's R2:	0.234	Efron's R2:	0.175
Variance of y*:	4.295	Variance of error:	3.290
Count R2:	0.779	Adj Count R2:	0.140
AIC:	0.992	AIC*n:	359.026
BIC:	-1762.075	BIC':	-47.723

```

221 .
222 . scalar SigDoseFw1 = "no"

223 . scalar MainEffwkFw1 = "bf4 age"

224 . ***** Moderator analysis for Dose=>paid employment wave one
225 . title4 "testing potential moderators for women and hp2work in wave 1"

```

testing potential moderators for women and hp2work in wave 1

```

226 . set more off

227 . forvalues j=1/1 {
      2.          sw, pr(.1):logistic HP2work age occ1w1-occ8w1 bf8 illw`j'
>   shjobw`j' havmilsq ///
>          avgcumdosew`j' ageXd1 if gender==2, coef
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.9407 >= 0.1000 removing occ4w1
p = 0.7880 >= 0.1000 removing shjobw1
p = 0.7709 >= 0.1000 removing bf8
p = 0.7819 >= 0.1000 removing occ7w1
p = 0.7309 >= 0.1000 removing occ3w1
p = 0.6557 >= 0.1000 removing havmilsq
p = 0.3777 >= 0.1000 removing occ6w1
p = 0.4099 >= 0.1000 removing occ2w1
p = 0.2835 >= 0.1000 removing occ1w1
p = 0.1994 >= 0.1000 removing occ5w1
p = 0.1230 >= 0.1000 removing ageXd1
p = 0.1760 >= 0.1000 removing illw1
p = 0.1245 >= 0.1000 removing occ8w1
p = 0.1089 >= 0.1000 removing avgcumdosew1

```

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	41.64
	Prob > chi2	=	0.0000
Log likelihood = -185.74123	Pseudo R2	=	0.1008

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0695394	.011616	5.99	0.000	.0467724	.0923064
_cons	-4.709665	.6434135	-7.32	0.000	-5.970733	-3.448598

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	20	14	34
-	73	256	329
Total	93	270	363

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

Sensitivity	$\Pr(+ D)$	21.51%
Specificity	$\Pr(- \sim D)$	94.81%
Positive predictive value	$\Pr(D +)$	58.82%
Negative predictive value	$\Pr(\sim D -)$	77.81%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.19%
False - rate for true D	$\Pr(- D)$	78.49%
False + rate for classified +	$\Pr(\sim D +)$	41.18%
False - rate for classified -	$\Pr(D -)$	22.19%
Correctly classified		76.03%

Logistic model for HP2work, goodness-of-fit test

number of observations =	363
number of covariate patterns =	49
Pearson $\chi^2(47)$ =	58.17
Prob > χ^2 =	0.1274

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-206.563	Log-Lik Full Model:	-185.741
D(361):	371.482	LR(1):	41.643
		Prob > LR:	0.000
McFadden's R2:	0.101	McFadden's Adj R2:	0.091
Maximum Likelihood R2:	0.108	Cragg & Uhler's R2:	0.159
McKelvey and Zavoina's R2:	0.172	Efron's R2:	0.125
Variance of y*:	3.971	Variance of error:	3.290
Count R2:	0.760	Adj Count R2:	0.065
AIC:	1.034	AIC*n:	375.482
BIC:	-1756.397	BIC':	-35.748

```

228 .
229 . * capturing significant vars
230 . local cn5: colnames(e(b))

231 . di "`cn5'"
      age _cons

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

233 . di `leng5'
      9

234 . local leng5b `leng5'-6

235 . di `leng5b'
      3

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

237 . di "`nuvlist5'"
      age

238 . local rhsvars5 = "`nuvlist2'"

239 . local nuvlist6= "`nuvlist2'"

240 . local nuvlist6= substr("`cn5'",1,`leng5b')

241 . di "`nuvlist6'"
      age

242 .
243 . foreach varx in `nuvlist6' {
      2. cap gen `varx'X`vary' = `varx'*avgcumdosew1
      3. }

244 .

```

```
245 . cap gen illw1Xd1 = illw1*avgcumdosew1
```

```
246 .
```

```
247 . logit hp2hmcare age avgcumdosew1 illw1 ageXd1 illw1Xd1 if gender==2
>      // correct regress on previous
```

```
Iteration 0:  log likelihood = -233.72859
Iteration 1:  log likelihood = -189.61734
Iteration 2:  log likelihood = -188.76377
Iteration 3:  log likelihood = -188.76057
Iteration 4:  log likelihood = -188.76057
```

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(5)      =          89.94
                                                    Prob > chi2     =          0.0000
Log likelihood = -188.76057                        Pseudo R2      =          0.1924
```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0970647	.0160129	6.06	0.000	.0656799	.1284495
avgcumdosew1	.884954	2.296761	0.39	0.700	-3.616615	5.386523
illw1	.9418439	.3176563	2.96	0.003	.319249	1.564439
ageXd1	-.0212632	.0412659	-0.52	0.606	-.1021429	.0596166
illw1Xd1	-.2742628	.427414	-0.64	0.521	-1.111979	.5634532
_cons	-5.742044	.8635113	-6.65	0.000	-7.434495	-4.049593

```
248 .
```

```
249 .
```

```
250 . scalar SigDoseWkFw1 = "no"
```

```
251 . scalar SigDoseWkMw1 = "no"
```

```
252 . 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)

```

253 . scalar MainEffwkMw1 = "bf4 bf40"

254 . scalar MainEffwkFw1 = "age "

255 . scalar WKModMw1 = "none"

256 . scalar WkModFw1 = "ageXd1"

257 .
258 .
259 . * male sign main effects in main effects model: 2- bf4, bf40
260 . * male and female main effects model avgcumdosew1 were not signif.
261 . * male hp2wk w1 mediators: bf4 and bf40
262 . * female signif main effects in main effects model
263 .
264 . title4 "H1 pt 2 wave 1 Mediation of paid employment testing for males"

```

H1 pt 2 wave 1 Mediation of paid employment testing for males

```

265 .
266 . * male hp2wk w1 mediators: testing b4 and b40
267 .
268 . cap gen ageXillw1 = age*illw1

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

```

	bf4	age
bf4	1.0000	
age	-0.4041	1.0000

```

270 .
271 .
272 . glm age avgcumdosew1 if gender==1, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-1331.608**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	148.5632
Deviance	=	50214.37624	(1/df) Deviance = 148.5632
Pearson	=	50214.37624	(1/df) Pearson = 148.5632
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		

Log likelihood	= -1331.607976	<u>AIC</u>	= 7.844753
		<u>BIC</u>	= 48244.19

	OIM					
age	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
273 . 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 : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 332.2034085	(1/df) Deviance	=	.9828503
Pearson = 339.5831812	(1/df) Pearson	=	1.004684

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

```

274 .
275 .
276 . des bf4

```

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

```

277 . glm bf4 avgcumdosew1 if gender==1, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-1026.9659**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
Deviance	= 8366.946191	Scale parameter	=	24.75428
Pearson	= 8366.946191	(1/df) Deviance	=	24.75428
		(1/df) Pearson	=	24.75428
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	6.05274
Log likelihood	= -1026.965868	<u>BIC</u>	=	6396.763

bf4	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	-.1031788	.161925	-0.64	0.524	-.4205461	.2141884
_cons	12.54134	.2786337	45.01	0.000	11.99523	13.08746

```

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

```

Iteration 1: deviance = **302.5414**
 Iteration 2: deviance = **301.6138**
 Iteration 3: deviance = **301.6078**
 Iteration 4: deviance = **301.6078**
 Iteration 5: deviance = **301.6078**

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 301.6078179	(1/df) Deviance	=	.8923308
Pearson	= 318.2302284	(1/df) Pearson	=	.9415096

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1668.576

hp2work	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.1012401	.0146623	-6.90	0.000	-.1299776	-.0725026
_cons	.3470813	.1825598	1.90	0.057	-.0107293	.704892

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

279 .
 280 .
 281 .
 282 .
 283 . des bf40

variable name	storage type	display format	value label	variable label
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

284 . glm bf40 avgcumdosew1 if gender==1, fam(gauss) link(identity)

Iteration 0: log likelihood = -659.60303

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	2.852057
Deviance = 963.9952523	(1/df) Deviance	=	2.852057
Pearson = 963.9952523	(1/df) Pearson	=	2.852057

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

	<u>AIC</u>	=	3.891783
Log likelihood = -659.6030291	<u>BIC</u>	=	-1006.188

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.0453656	.0549627	0.83	0.409	-.0623593	.1530904
_cons	2.124647	.0945774	22.46	0.000	1.939278	2.310015

```
285 . glm hp2work bf40 if gender==1, fam(binomial) link(probit) ///
>      irls scale(dev)
```

```
Iteration 1:  deviance = 316.1036
Iteration 2:  deviance = 315.5033
Iteration 3:  deviance = 315.5021
Iteration 4:  deviance = 315.5021
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 315.5020956	(1/df) Deviance	=	.9334382
Pearson = 333.9910612	(1/df) Pearson	=	.9881392

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

BIC = -1654.682

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.2493852	.044782	5.57	0.000	.161614	.3371563
_cons	-1.421911	.1366145	-10.41	0.000	-1.689671	-1.154152

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

```
286 . title4 "bf40 could be mediator for males h2wk in wave 1"
```

```
bf40 could be mediator for males h2wk in wave 1
```

```

287 .
288 .
289 .
290 . glm illw1 avgcumdosew1 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-151.48261**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	.1435742
Deviance	= 48.52808533	(1/df) Deviance	=	.1435742
Pearson	= 48.52808533	(1/df) Pearson	=	.1435742
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]
		<u>AIC</u>	=	.9028389
Log likelihood	= -151.4826069	<u>BIC</u>	=	-1921.656

illw1	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	.0087277	.0123318	0.71	0.479	-.0154423	.0328976
_cons	.0962541	.0212201	4.54	0.000	.0546635	.1378446

```

291 . glm hp2work illw1 if gender==1, fam(binomial) irls ///
> scale(dev) link(probit)

```

Iteration 1: deviance = **345.5327**
 Iteration 2: deviance = **345.2889**
 Iteration 3: deviance = **345.2888**
 Iteration 4: deviance = **345.2888**

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 345.2887981	(1/df) Deviance	=	1.021564
Pearson	= 340.1227725	(1/df) Pearson	=	1.00628
Variance function:	V(u) = u*(1-u)			[Bernoulli]
Link function	: g(u) = invnorm(u)			[Probit]
		<u>BIC</u>	=	-1624.895

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw1	.1303424	.1949057	0.67	0.504	-.2516658	.5123505
_cons	-.8347401	.080778	-10.33	0.000	-.993062	-.6764181

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

```

292 .
293 . scalar WkMedMw1 = "bf40"

294 .
295 .
296 .
297 . title4 "Testing possible female paid employment mediators for paid employmen
> t in wave 1"

```

Testing possible female paid employment mediators for paid employment in wave
> 1

```

298 .
299 . title4 "Test of age as possible female mediator in wave 1"

```

Test of age as possible female mediator in wave 1

```

300 . glm age avgcumdosew1 if gender==2, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-1406.325**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.455
Deviance = 49260.25928	(1/df) Deviance	=	136.455
Pearson = 49260.25928	(1/df) Pearson	=	136.455

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

Log likelihood = -1406.325011	<u>AIC</u>	=	7.759366
	<u>BIC</u>	=	47132.38

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```
301 . 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      : ML 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.)

```
302 . title4 "age can be a wave 1 mediator for women with hp2work "
```

```
age can be a wave 1 mediator for women with hp2work
```

```

303 .
304 .
305 . title4 "Test of b40 as female mediator of paid employment in wave 1"

```

Test of b40 as female mediator of paid employment in wave 1

```

306 . glm bf40 avgcumdosew1 if gender==2, fam(gauss) link(identity)

```

Iteration 0: log likelihood = **-818.49948**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	5.351018
Deviance = 1931.717442	(1/df) Deviance	=	5.351018
Pearson = 1931.717442	(1/df) Pearson	=	5.351018

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

	<u>AIC</u>	=	4.520658
Log likelihood = -818.4994757	<u>BIC</u>	=	-196.162

bf40	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	.4524905	.2213302	2.04	0.041	.0186913	.8862898
_cons	3.013471	.1423225	21.17	0.000	2.734524	3.292417

```

307 . 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.)

308 . title4 "b40 could be a wv 1 mediator for women"

b40 could be a wv 1 mediator for women

309 .

310 .

311 . title4 "bf4 Test of female mediation of paid employment in wave 1"

bf4 Test of female mediation of paid employment in wave 1

312 . glm bf4 avgcumdosew1 if gender==2, fam(gauss) link(identity)

Iteration 0: log likelihood = **-1109.0162**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.52082
Deviance = 9574.015672	(1/df) Deviance	=	26.52082
Pearson = 9574.015672	(1/df) Pearson	=	26.52082
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	6.121302
Log likelihood = -1109.016226	<u>BIC</u>	=	7446.136

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```
313 . 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      :  MQL 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
```

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

```
314 . title4 "bf4 alone is a mediator for women"
```

```
bf4 alone is a mediator for women
```

```
315 .
```

```
316 .
```

```
317 . title "bf4 Test of female mediation of paid employment in wave 1"
```

```
*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****      bf4 Test of female mediation of paid employment in wave 1      ****
> *
*****                                     ****
> *
```

```

*****
> *
*****
18 Jun 2012    18:12:37    *****
> *
*****
> *
*****
> *

```

```
318 . glm bf4 avgcumdosew1 if gender==2, fam(gauss) link(identity)
```

```
Iteration 0:    log likelihood = -1109.0162
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.52082
Deviance = 9574.015672	(1/df) Deviance	=	26.52082
Pearson = 9574.015672	(1/df) Pearson	=	26.52082

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

Log likelihood	= -1109.016226	<u>AIC</u>	= 6.121302
		<u>BIC</u>	= 7446.136

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```
319 . 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
	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.)

```
320 . title4 "bf4 could be a mediator for women"
```

bf4 could be a mediator for women

321 .

322 .

323 .

```
324 . title "Test of female mediation of illw1 and paid employment in wave 1"
```

```
*****
> *
*****
> *
*****
> *
***** Test of female mediation of illw1 and paid employment in wave 1 ****
> *
*****
> *
*****
> *
*****
18 Jun 2012      18:12:40 *****
> *
*****
> *
```

```
325 . glm illw1 avgcumdosew1 if gender==2, fam(gauss) link(identity)
```

```
Iteration 0: log likelihood = -259.70777
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.2462383
Deviance = 88.89203958	(1/df) Deviance	=	.2462383
Pearson = 88.89203958	(1/df) Pearson	=	.2462383

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

	<u>AIC</u>	=	1.441916
Log likelihood = -259.7077741	<u>BIC</u>	=	-2038.987

illw1	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew1	.0655142	.0474789	1.38	0.168	-.0275426	.1585711	
_cons	.1570822	.0305304	5.15	0.000	.0972436	.2169207	

```
326 . glm hp2work illw1 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1: deviance = 408.8941
Iteration 2: deviance = 408.3909
Iteration 3: deviance = 408.3907
Iteration 4: deviance = 408.3907
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 408.3907209	(1/df) Deviance	=	1.131276
Pearson = 362.2934789	(1/df) Pearson	=	1.003583

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

	BIC	=	-1719.489
--	-----	---	-----------


```
333 . mvreg bf4 age bf40 = avgcumdosew1 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.149837	0.0253	9.376729	0.0024
age	363	2	11.6814	0.0338	12.64139	0.0004
bf40	363	2	2.313227	0.0114	4.179627	0.0416

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.477832	-.5398375
_cons	10.99384	.3168463	34.70	0.000	10.37075	11.61694
age						
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.775898	6.171859
_cons	48.88157	.7187038	68.01	0.000	47.4682	50.29494
bf40						
avgcumdosew1	.4524905	.2213302	2.04	0.042	.017232	.887749
_cons	3.013471	.1423225	21.17	0.000	2.733585	3.293356

```
334 . 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
```



```
341 . mvreg bf4 age bf40 illw1 = avgcumdosew1 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.149837	0.0253	9.376729	0.0024
age	363	2	11.6814	0.0338	12.64139	0.0004
bf40	363	2	2.313227	0.0114	4.179627	0.0416
illw1	363	2	.4962241	0.0052	1.904017	0.1685

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.477832	-.5398375
_cons	10.99384	.3168463	34.70	0.000	10.37075	11.61694
age						
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.775898	6.171859
_cons	48.88157	.7187038	68.01	0.000	47.4682	50.29494
bf40						
avgcumdosew1	.4524905	.2213302	2.04	0.042	.017232	.887749
_cons	3.013471	.1423225	21.17	0.000	2.733585	3.293356
illw1						
avgcumdosew1	.0655142	.0474789	1.38	0.168	-.0278557	.1588841
_cons	.1570822	.0305304	5.15	0.000	.0970423	.217122

```
342 . glm hp2work bf4 age bf40 illw1 if gender==2, fam(binomial) ///
> link(probit) irls scale(dev)
```

```
Iteration 1: deviance = 354.001
Iteration 2: deviance = 352.9698
Iteration 3: deviance = 352.9654
Iteration 4: deviance = 352.9654
Iteration 5: deviance = 352.9654
```

```
Generalized linear models
Optimization : MQL Fisher scoring
               (IRLS EIM)
Deviance     = 352.965421
Pearson      = 374.1304084
```

```
No. of obs      = 363
Residual df     = 358
Scale parameter = 1
(1/df) Deviance = .9859369
(1/df) Pearson  = 1.045057
```

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

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

```
BIC = -1757.231
```

hp2work	EIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
bf4	-.0628029	.0158842	-3.95	0.000	-.0939353	-.0316706	
age	.0280305	.0070628	3.97	0.000	.0141877	.0418734	
bf40	.0276234	.0334236	0.83	0.409	-.0378856	.0931324	
illw1	.0692009	.1432947	0.48	0.629	-.2116515	.3500534	
_cons	-1.60672	.4655573	-3.45	0.001	-2.519195	-.6942446	

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

```

343 . qui: {
      When all are together only age and b4 are a wave 1 mediators for women

344 .
345 .
346 . scalar wkMedMw1 = "bf40 "

347 .
348 . scalar SigDoseWkMw1 = "no"

349 . scalar MainEffwkMw1 = "age"

350 . scalar MainEffwkFw1 = "age"

351 . scalar wkMedFw1 = "age b4"

352 . * male hp2wk w1 mediators:  testing b4 and b40
353 .
354 . title4 "*---1.- Summary matrix construction Paid employment partition: first
      > two rows"

```

```

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

```

```

355 .

```

```

356 .      matrix define wkMw1 = J(1,8, 0)

357 .      matrix define  wkFw1 = J(1,8, 0)

358 . matrix colnames  wkMw1=  hypnum ptnum wave gender medsig numMA sig numModsig
    > numMed

359 . matrix colnames  wkFw1=  hypnum ptnum wave gender medsig numMA sig numModsig
    > numMed

360 .      matrix rownames  wkMw1 = workMw1

361 .      matrix rownames  wkFw1 = workFw1

362 .      matrix define  wkMw1= (1, 2, 1, 1, 0 ,2,  0  , 1 )

363 .      matrix define  wkFw1= (1, 2, 1, 2, 0, 1,  1  , 2 )

364 .

365 .      matrix define H1pt2w1 = ( wkMw1 \  wkFw1)

366 .      matrix colnames H1pt2w1 =  hypnum ptnum wave  medsig numMA sig numModsig
    > numMed

367 .      matrix rownames H1pt2w1 =  wkMw1 wkFw1

368 .      matlist H1pt2w1

```

		hypnum	ptnum	wave	medsig	numMA sig	numModsi
> g	numMed	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2	0	1					
	wkFw1	1	2	1	2	0	
> 1	1	2					

```

369 .
370 . set more off

371 . scalar list
    MainEffwkFw1 = age
    MainEffwkMw1 = age
    MainEffVactnMw1 = age radhlw1
    VactnMedFw1 = age illw1 radhlw1
    VactnMedMw1 = age
    VacatnModFw1 = none
    MainEffVactnFw1 = age radhlw1 bf7m
    SigDoseVactnFw1 = no
    VactnModMw1 = none
    inthobMedFw1 = age bf4 illw1 bf4m
    inthobMedMw1 = age
    inthobMw1 = age
    InthbModFw1 = none
    MainEffInthbFw1 = age radhlw1 bf4
    SigDoseInthbFw1 = no
    InthbModMw1 = none
    MainEffInthbMw1 = age radhlw1 shfamw1
    SigDoseInthbMw1 = no
    MainEffMw1 = radhlw1 bf4 bf40
    sxlifeMedMw1 = radhlw1
    sxlifeMedFw1 = age illw1 radhlw1 bf4 bf4m
    MainEffsxlifeFw1 = age bf4 bf4m
    SigDoseSxlifeFw1 = no
    SigDosesxlifeMw1 = no
    MainEffsxlifeMw1 = age bf4 bf40
    MainEffhmcrFw1 = age
    MainEffhmcrMw1 = age
    hmcrMedFw1 = age bf4
    hmcrMedMw1 = radhlw1
    SigDosePrbfmhmMw1 = no
    vactnModMw1 = none
    SigDoseVactnMw1 = no
    SxLifeModFw1 = no
    sxlifeModFw1 = none
    sxlifeModMw1 = none
    MaineffhmcrMw1 = age bf4 bf40
    SigDoseMEhmcrW1 = no
    PrbfmhmMedFw1 = age bf4
    PrbfmhmMedMw1 = age
    MainEffPrbfmhmFw1 = age radhlw1 bf4
    MainEffPrbfmhmMw1 = age bf4
    PrbfmhmModFw1 = none
    PrbfmhmModMw1 = none
    SigDosePrbfmhmFw1 = no
    SigDosePrbfhmMw1 = no

```

```

MainEffPrbfhmMw1 = age bf4
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
MainEffPrbsocMw1 = age bf4m
SigdoseMw1 = no
ProbsocMedFw1 = age bf4
ProbsocMedMw1 = radhlw1
ProbsocModFw1 = none
SigDoseProbsocMw1 = no
hmcrmedMw1 = radhlw1
hmcrmedFw1 = age b4 b40
SigdosehmcrFw1 = no
MainEffProbSocFw1 = age radhlw1 avgcumdosew1 shrelaw1 bf4
SigDoseProbsocFw1 = yes
PrbsocModMw1 = shjobw1Xd1 shrelaw1Xd1
    WkhmcrMw1 = age b4
    WkModFw1 = ageXd1
hmcareMedFw1 = age illw1
hmcareMedMw1 = age
SigDosehmcrFw1 = no
    wkMedMw1 = bf40
hmcrModFw1 = none
SigDoseHmcrFw1 = yes
    WkMedMw1 = bf40
hmcrModMw1 = none
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
    WkModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
VactnMedMw2 = age
inthobMedMw2 = age
    inthobMw2 = age
PrbfhmModMw2 = 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
MainEfffwkFw3 = age
MainEfffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no

```

```

372 . * moderator construction
373 . * none ussed because basic dose work relationship washes out
374 .
375 . title "2. Hyp 1 pt 2 wave 1 male dose Hp2hmcare impact explored"

```

```

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

```

```

*****                               18 Jun 2012    18:12:48    ****
> *
*****
> *
*****
> *

```

```

376 .
377 . * ----- testing male and female moderators-wave 1 for hmcare-----
> ----
378 .
379 . cap gen hp2hmcare=HP2hmcare

380 .
381 . forvalues j=1/1 {
      2. set more off
      3. local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
      4. di as input "For females hp2hmcare on wave 1 with dose ns"
      5.       des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' bf8 /
> //
>       marrw`j'1-marrw`j'6 `w1bf' 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 1 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w1	double	%15.0g	LABJ	profess executive administration in 1986
occ2w1	double	%15.0g	LABJ	technical sales admin support in 1986
occ3w1	double	%15.0g	LABJ	service occup protective services in 1986
occ4w1	double	%15.0g	LABJ	precision prod mechan craft construction in 1986
occ5w1	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1986
occ6w1	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1986

occ7w1	double	%15.0g	LABJ	homemaking or caregiving in 1986
occ8w1	double	%15.0g	LABJ	student in 1986
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
avgcumdosew1	double	%8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986
bf8	float	%9.0g		$bf8 = \max(0, radtlw3 - 40) * bf5m$
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
bf1	float	%9.0g		$bf1 = \max(0, kzchorn - 40)$
bf4	float	%9.0g		$bf4 = \max(0, 24 - BSIsoma)$
bf9	float	%9.0g		$bf9 = \max(0, 30 - shhlw1)$
bf10	float	%9.0g		$bf10 = \max(0, sufamw1 - 20)$
bf11	float	%9.0g		$bf11 = \max(0, 20 - sufamw1)$
bf4m	float	%9.0g		$bf4m = \max(0, 32 - BSIsoma)$
bf15m	float	%9.0g		$bf15m = \max(0, 1 - icdxcnt) * bf2$
bf20	float	%9.0g		$bf20 = \max(0, kzchorn - 2.53946E-006)$
bf22	float	%9.0g		$bf22 = \max(0, icdxcnt - 1.01635E-007) * bf7m$
bf30	float	%9.0g		$bf30 = \max(0, neiwl - 85) * bf20$
bf40	float	%9.0g		$bf40 = \max(0, icdxcnt - 1.01635E-007)$
radhlw1	double	%8.0g		how much believed personal health is affected by radiation in 1986

note: marrw14 dropped because of collinearity
 note: marrw16 dropped because of collinearity
 begin with full model

p = **0.8518** >= 0.1000 removing **marrw13**
 p = **0.6179** >= 0.1000 removing **avgcumdosew1**
 p = **0.5000** >= 0.1000 removing **havmilsq**
 p = **0.5276** >= 0.1000 removing **bf8**
 p = **0.5433** >= 0.1000 removing **illw1**
 p = **0.4921** >= 0.1000 removing **marrw15**
 p = **0.1693** >= 0.1000 removing **suprtw1**

Logistic regression

Number of obs = 340

LR chi2(2) = 41.30

Prob > chi2 = 0.0000

Log likelihood = -152.22537

Pseudo R2 = 0.1194

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0525652	.0122122	4.30	0.000	.0286297	.0765007
shjobw1	.0156714	.0041469	3.78	0.000	.0075436	.0237992
_cons	-4.957356	.7134246	-6.95	0.000	-6.355643	-3.55907

Logistic model for hp2hmcare, goodness-of-fit test

number of observations = 340
number of covariate patterns = 215
Pearson chi2(212) = 221.53
Prob > chi2 = 0.3127

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	14	4	18
-	56	266	322
Total	70	270	340

Classified + if predicted Pr(D) >= .5

True D defined as hp2hmcare != 0

Sensitivity	Pr(+ D)	20.00%
Specificity	Pr(- ~D)	98.52%
Positive predictive value	Pr(D +)	77.78%
Negative predictive value	Pr(~D -)	82.61%

False + rate for true ~D	Pr(+ ~D)	1.48%
False - rate for true D	Pr(- D)	80.00%
False + rate for classified +	Pr(~D +)	22.22%
False - rate for classified -	Pr(D -)	17.39%

Correctly classified 82.35%

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

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-152.225
D(337):	304.451	LR(2):	41.295
		Prob > LR:	0.000
McFadden's R2:	0.119	McFadden's Adj R2:	0.102
Maximum Likelihood R2:	0.114	Cragg & Uhler's R2:	0.179
McKelvey and Zavoina's R2:	0.217	Efron's R2:	0.130
Variance of y*:	4.204	Variance of error:	3.290
Count R2:	0.824	Adj Count R2:	0.143
AIC:	0.913	AIC*n:	310.451
BIC:	-1659.904	BIC':	-29.637

```

382 .
383 . cap gen shjobw1Xd1 = shjobw1*avgcumdosew1

384 .
385 . logit hp2hmcare age avgcumdosew1 shjobw1 ageXd1 shjobw1Xd1 if gender==1

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -152.72837
Iteration 2:  log likelihood = -151.52069
Iteration 3:  log likelihood = -151.51061
Iteration 4:  log likelihood = -151.51059
Iteration 5:  log likelihood = -151.51059

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	42.72
	Prob > chi2	=	0.0000
Log likelihood = -151.51059	Pseudo R2	=	0.1236

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0459744	.0152127	3.02	0.003	.0161581	.0757907
avgcumdosew1	-2.020359	2.276313	-0.89	0.375	-6.481851	2.441132
shjobw1	.0138632	.0047443	2.92	0.003	.0045646	.0231618
ageXd1	.0271336	.0358792	0.76	0.449	-.0431882	.0974555
shjobw1Xd1	.0056837	.007561	0.75	0.452	-.0091355	.020503
_cons	-4.439055	.908991	-4.88	0.000	-6.220645	-2.657466

```

386 .
387 . scalar SigDosehmcMw1 = "no"

388 . scalar MainEffhmcMw1 = "age shjobw1"

389 . scalar hmcModMw1 = "none"

390 .
391 .
392 .
393 . title4 "Trimmed female Hp2hmcare moderator model"

```

```

Trimmed female Hp2hmcare moderator model

```

```

394 .
395 . cap gen ageXd1= age*avgcumdosew1

396 .
397 . forvalues j=1/1 {
      2. set more off
      3. local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
      4. di as input "For females HP2hmcare on wave 1 with dose ns"
      5.         des age avgcumdosew`j' ///
>         marrw`j'1-marrw`j'6 `w1bf' radhlw`j'
      6.         logistic hp2hmcare marrw`j'3-marrw`j'6 age havmilsq ///
>         avgcumdosew1 illw`j' ageXd1 if gender==2, coef
      7.         estat gof
      8.         estat class
      9.         fitstat
     10.         }
For females HP2hmcare on wave 1 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
avgcumdosew1	double	%8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
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)
bf10	float	%9.0g		bf10= max(0, sufamw1 - 20)

```

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
bf20          float   %9.0g          bf20 = max(0, kzchorn -
                                     2.53946E-006)
bf22          float   %9.0g          bf22 = max(0, icdxcnt -
                                     1.01635E-007) * bf7m
bf30          float   %9.0g          bf30 = max(0, neiwl - 85) * bf20
bf40          float   %9.0g          bf40 = max(0, icdxcnt -
                                     1.01635E-007)
radhlw1       double  %8.0g          how much believed personal
                                     health is affected by
                                     radiation in 1986

```

note: marrw14 != 0 predicts success perfectly
marrw14 dropped and 3 obs not used

```

Logistic regression                                Number of obs   =          360
                                                    LR chi2(8)      =          90.30
                                                    Prob > chi2     =          0.0000
Log likelihood = -185.35656                      Pseudo R2      =          0.1959

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
marrw13	-.3849014	.3723136	-1.03	0.301	-1.114623	.3448198
marrw14	0	(omitted)				
marrw15	-.9153623	1.029513	-0.89	0.374	-2.93317	1.102445
marrw16	-.9459556	1.17984	-0.80	0.423	-3.258399	1.366488
age	.1113504	.0191706	5.81	0.000	.0737767	.1489241
havmilsq	-2.13e-06	2.61e-06	-0.82	0.413	-7.24e-06	2.97e-06
avgcumdosew1	1.596621	2.0241	0.79	0.430	-2.370543	5.563785
illw1	.8779977	.2787263	3.15	0.002	.3317043	1.424291
ageXd1	-.0367027	.0350736	-1.05	0.295	-.1054456	.0320402
_cons	-6.146477	.9034853	-6.80	0.000	-7.917275	-4.375678

Note: 1 failure and 0 successes completely determined.

Logistic model for hp2hmcare, goodness-of-fit test

```

number of observations =          360
number of covariate patterns =        338
Pearson chi2(329) =        329.08
Prob > chi2 =          0.4884

```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	61	28	89
-	61	210	271
Total	122	238	360

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

True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	50.00%
Specificity	$\Pr(- \sim D)$	88.24%
Positive predictive value	$\Pr(D +)$	68.54%
Negative predictive value	$\Pr(\sim D -)$	77.49%
False + rate for true ~D	$\Pr(+ \sim D)$	11.76%
False - rate for true D	$\Pr(- D)$	50.00%
False + rate for classified +	$\Pr(\sim D +)$	31.46%
False - rate for classified -	$\Pr(D -)$	22.51%
Correctly classified		75.28%

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

Log-Lik Intercept Only:	-230.506	Log-Lik Full Model:	-185.357
D(350):	370.713	LR(8):	90.300
		Prob > LR:	0.000
McFadden's R2:	0.196	McFadden's Adj R2:	0.152
Maximum Likelihood R2:	0.222	Cragg & Uhler's R2:	0.307
McKelvey and Zavoina's R2:	0.468	Efron's R2:	0.243
Variance of y*:	6.185	Variance of error:	3.290
Count R2:	0.753	Adj Count R2:	0.270
AIC:	1.085	AIC*n:	390.713
BIC:	-1689.423	BIC':	-43.211

```

398 .
399 . title4 "Trimmed model of hp2work for women in wave 1"

```

Trimmed model of hp2work for women in wave 1

```

400 . forvalues j=1/1 {
      2. set more off
      3. local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
      4. di as input "For females HP2hmcare on wave 1 with dose ns"
      5.       des age avgcumdosew`j' ///
>       marrw`j'1-marrw`j'6 `w1bf' radhlw`j'
      6.       logistic hp2hmcare age avgcumdosew1 illw`j' if gender==2, coef
      7.       estat gof
      8.       estat class
      9.       fitstat
     10.       }

```

For females HP2hmcare on wave 1 with dose ns

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
avgcumdosew1	double	%8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
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)
bf10	float	%9.0g		bf10= max(0, sufamw1 - 20)
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
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)
radhlw1	double	%8.0g		how much believed personal health is affected by radiation in 1986

Logistic regression

Number of obs = 363

LR chi2(3) = 88.59

Prob > chi2 = 0.0000

Log likelihood = -189.43609

Pseudo R2 = 0.1895

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0919881	.0122684	7.50	0.000	.0679425	.1160337
avgcumdosew1	-.5411658	.2831823	-1.91	0.056	-1.096193	.0138613
illw1	.8054954	.2675545	3.01	0.003	.2810981	1.329893
_cons	-5.38915	.6535341	-8.25	0.000	-6.670053	-4.108247

Logistic model for hp2hmcare, goodness-of-fit test

number of observations = 363
number of covariate patterns = 313
Pearson chi2(309) = 323.98
Prob > chi2 = 0.2677

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	64	28	92
-	61	210	271
Total	125	238	363

Classified + if predicted Pr(D) >= .5

True D defined as hp2hmcare != 0

Sensitivity	Pr(+ D)	51.20%
Specificity	Pr(- ~D)	88.24%
Positive predictive value	Pr(D +)	69.57%
Negative predictive value	Pr(~D -)	77.49%

False + rate for true ~D	Pr(+ ~D)	11.76%
False - rate for true D	Pr(- D)	48.80%
False + rate for classified +	Pr(~D +)	30.43%
False - rate for classified -	Pr(D -)	22.51%

Correctly classified 75.48%

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

Log-Lik Intercept Only:	-233.729	Log-Lik Full Model:	-189.436
D(359):	378.872	LR(3):	88.585
		Prob > LR:	0.000
McFadden's R2:	0.190	McFadden's Adj R2:	0.172
Maximum Likelihood R2:	0.217	Cragg & Uhler's R2:	0.299
McKelvey and Zavoina's R2:	0.304	Efron's R2:	0.241
Variance of y*:	4.725	Variance of error:	3.290
Count R2:	0.755	Adj Count R2:	0.288
AIC:	1.066	AIC*n:	386.872
BIC:	-1737.218	BIC':	-70.902

401 .

402 . 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.

403 . 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)

404 . scalar SigDosehmcFw1 = "no"

405 . scalar MainEffhmcFw1 = "illw1 age"

406 .

407 .

408 . title4 "home care wave 1 male mediator analysis"

home care wave 1 male mediator analysis

409 .

410 . title4 "age is a possible male mediator of home care in wave 1"

age is a possible male mediator of home care in wave 1

411 . glm age avgcumdosew1 if gender==1, fam(gaussian) link(identity)

Iteration 0: log likelihood = **-1331.608**

Generalized linear models

Optimization : **ML**

Deviance = **50214.37624**

Pearson = **50214.37624**

No. of obs = **340**

Residual df = **338**

Scale parameter = **148.5632**

(1/df) Deviance = **148.5632**

(1/df) Pearson = **148.5632**

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

[**Gaussian**]

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

[**Identity**]

Log likelihood = **-1331.607976**

AIC = **7.844753**

BIC = **48244.19**

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

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

```
Iteration 1:  deviance = 320.8295
Iteration 2:  deviance = 320.0337
Iteration 3:  deviance = 320.0328
Iteration 4:  deviance = 320.0328
```

```
Generalized linear models               No. of obs      =       340
Optimization      :  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) = 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.)

```
413 .
414 . scalar hmcrMedMw1 = "age ageXillw1"

415 .
416 . di as input "age is a possible male mediator for home care in wave 1"
    age is a possible male mediator for home care in wave 1

417 .
418 .
419 . di as input "age and illw1 as main effects together suppress illw1"
    age and illw1 as main effects together suppress illw1
```

```
420 . glm illw1 age avgcumdosew1 if gender==1, family(gaussian) link(identity)
```

```
Iteration 0: log likelihood = -149.77052
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	337
		Scale parameter	=	.1425573
Deviance	= 48.04180784	(1/df) Deviance	=	.1425573
Pearson	= 48.04180784	(1/df) Pearson	=	.1425573

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

	<u>AIC</u>	=	.8986501
Log likelihood = -149.7705231	<u>BIC</u>	=	-1916.313

illw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0031119	.0016849	1.85	0.065	-.0001905	.0064143
avgcumdosew1	.0066365	.0123401	0.54	0.591	-.0175497	.0308227
_cons	-.0558998	.0850529	-0.66	0.511	-.2226005	.1108009

```
421 . glm hp2hmcare illw1 age if gender==1, family(binomial) irls scale(dev) link
> (probit)
```

```
Iteration 1: deviance = 320.7839
Iteration 2: deviance = 319.9774
Iteration 3: deviance = 319.9764
Iteration 4: deviance = 319.9764
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	337
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 319.9764494	(1/df) Deviance	=	.949485
Pearson	= 341.9238822	(1/df) Pearson	=	1.014611

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

	BIC	=	-1644.378
--	-----	---	-----------

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw1	.0470226	.1922185	0.24	0.807	-.3297186	.4237639
age	.032421	.0064525	5.02	0.000	.0197743	.0450676
_cons	-2.482523	.34428	-7.21	0.000	-3.1573	-1.807747

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

```

422 .
423 .
424 . di as input "Interaction of age and wave 1 illness for males is mediator-mod
> erator on hmcare"
Interaction of age and wave 1 illness for males is mediator-moderator on hmcar
> e

425 .
426 . cap gen ageXillw1 = age*illw1

427 . glm illw1 avgcumdosew1 if gender==1, family(gaussian) link(identity)

```

Iteration 0: log likelihood = **-151.48261**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.1435742
Deviance = 48.52808533	(1/df) Deviance	=	.1435742
Pearson = 48.52808533	(1/df) Pearson	=	.1435742

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

	<u>AIC</u>	=	.9028389
Log likelihood = -151.4826069	<u>BIC</u>	=	-1921.656

illw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.0087277	.0123318	0.71	0.479	-.0154423	.0328976
_cons	.0962541	.0212201	4.54	0.000	.0546635	.1378446

```

428 . glm hp2hmcare illw1 avgcumdosew1 ageXillw1 if gender==1, family(binomial) //
> /
>      irls scale(dev) link(probit)

```

```

Iteration 1:  deviance =  344.1427
Iteration 2:  deviance =   343.92
Iteration 3:  deviance =  343.9199
Iteration 4:  deviance =  343.9199

```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 343.9198791	(1/df) Deviance	=	1.023571
Pearson = 339.000371	(1/df) Pearson	=	1.00893

```

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

```

BIC = -1614.606

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
illw1	-1.213319	1.209268	-1.00	0.316	-3.583441	1.156803
avgcumdosew1	-.0042013	.0484889	-0.09	0.931	-.0992378	.0908352
ageXillw1	.0242393	.0213349	1.14	0.256	-.0175764	.0660551
_cons	-.8321418	.0831923	-10.00	0.000	-.9951958	-.6690878

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

```

429 .
430 .
431 .
432 . * Saving mediators as scalars for Dose=work relationship
433 . **** female mediators of dose-paid employment: radhlw1, age, bf40, bf4m, bf4
> , bf1

```

```

434 .
435 . scalar hmcrMedMw1 = "age"

436 . scalar hmcrMedFw1 = "age avgcumdosew1 bf4 bf4m "

437 .
438 . cap gen hp2vacatn = HP2vacatn

439 .
440 .
441 . title "2. H1 pt2 wave 1 Dose female moderator Homecare impact "

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****      2. H1 pt2 wave 1 Dose female moderator Homecare impact      ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                18 Jun 2012    18:13:14    ****
> *
*****
> *
*****
> *

442 .

```

```

443 .
444 . * review of general model for men and women
445 .
446 . forvalues j=1/1 {
      2. set more off
      3.
447 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
448 .   foreach var in HP2hmcare {
      5.
449 . local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
      6.   title "chunk 3 H1 test pt 2 :Gender= `k' model Wave = `j' for `e(de
      > pvar)' "
      7.           di _skip(4)
      8.
450 .
451 .   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' radhlw1 ///
      >           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.
452 . }
      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
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating

marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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)

```

*****
> *
*****
> *
*****
> *
***** chunk 3 H1 test pt 2 :Gender= model Wave = 1 for hp2hmcare *****
> *
*****
> *
*****
> *
*****
> *
***** 18 Jun 2012 18:13:14 *****
> *
*****
> *
*****
> *

```

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
note: _Ieduc_8 omitted because of collinearity
note: radhlw1 omitted because of collinearity

Logistic regression Number of obs = 358
 LR chi2(51) = 163.36
 Prob > chi2 = 0.0000
Log likelihood = -149.9205 Pseudo R2 = 0.3527

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1322255	.0241652	5.47	0.000	.0848625	.1795885
_Ieduc_2	-10.0193	754.0186	-0.01	0.989	-1487.869	1467.83
_Ieduc_3	-10.49152	754.0185	-0.01	0.989	-1488.341	1467.358
_Ieduc_4	-8.71423	754.0188	-0.01	0.991	-1486.564	1469.135
_Ieduc_5	-10.4068	754.0186	-0.01	0.989	-1488.256	1467.443
_Ieduc_6	-10.68819	754.0185	-0.01	0.989	-1488.537	1467.161
_Ieduc_7	-10.94334	754.0203	-0.01	0.988	-1488.796	1466.909
_Ieduc_8	0	(omitted)				
occ1w1	-2.443994	1.415397	-1.73	0.084	-5.218121	.3301329
occ2w1	-2.519671	1.458446	-1.73	0.084	-5.378173	.3388315
occ3w1	-2.372771	1.446929	-1.64	0.101	-5.2087	.4631575
occ4w1	-3.256872	1.570864	-2.07	0.038	-6.335709	-.1780355
occ5w1	-3.906156	1.725894	-2.26	0.024	-7.288845	-.5234666
occ6w1	-5.192057	1.956306	-2.65	0.008	-9.026346	-1.357767
occ7w1	-.9645317	1.49363	-0.65	0.518	-3.891993	1.962929
occ8w1	-1.541951	1.448029	-1.06	0.287	-4.380037	1.296134
marrw11	-.4640303	1.925158	-0.24	0.810	-4.237272	3.309211
marrw12	-1.711412	2.266816	-0.75	0.450	-6.15429	2.731467
marrw13	-1.34516	1.914926	-0.70	0.482	-5.098345	2.408026
marrw15	-2.648889	2.280264	-1.16	0.245	-7.118125	1.820346
marrw16	-3.140349	2.467603	-1.27	0.203	-7.976762	1.696063
inc1w1	1.997721	1.384475	1.44	0.149	-.7157992	4.711242
inc2w1	2.374508	1.354203	1.75	0.080	-.2796802	5.028697
inc3w1	2.719588	1.365246	1.99	0.046	.0437547	5.395421
inc4w1	2.169417	1.522601	1.42	0.154	-.8148263	5.15366
radhlw1	.000015	.0054568	0.00	0.998	-.0106801	.0107101
havmil	-.003359	.0026195	-1.28	0.200	-.008493	.0017751
avgcumdosew1	-.9556895	.3881039	-2.46	0.014	-1.716359	-.1950199
bf1	-.0087777	.0246959	-0.36	0.722	-.0571808	.0396254
bf4	-.5899724	.228594	-2.58	0.010	-1.038008	-.1419365
bf9	-.0436396	.0223962	-1.95	0.051	-.0875353	.0002562
bf10	.0090231	.0130434	0.69	0.489	-.0165414	.0345877
bf11	.0532598	.0430698	1.24	0.216	-.0311554	.1376749
bf4m	.4051708	.2117859	1.91	0.056	-.0099218	.8202635
bf15m	.0002493	.0003321	0.75	0.453	-.0004015	.0009002
bf20	-.0059985	.0202682	-0.30	0.767	-.0457235	.0337264

bf22	-.0000321	.0000692	-0.46	0.643	-.0001678	.0001036
bf30	.0002449	.0002901	0.84	0.398	-.0003236	.0008135
bf40	.0632557	.0911174	0.69	0.488	-.115331	.2418425
deawl	.158171	.2197751	0.72	0.472	-.2725802	.5889222
dvcewl	.1254408	2.091225	0.06	0.952	-3.973284	4.224166
sepawl	-.6497514	2.414062	-0.27	0.788	-5.381225	4.081722
accdwl	.2831415	.8314301	0.34	0.733	-1.346432	1.912715
movewl	.2074149	.4471555	0.46	0.643	-.6689937	1.083823
radhlwl	0	(omitted)				
illwl	1.106215	.3492383	3.17	0.002	.4217202	1.790709
shfamwl	-.0002582	.0064446	-0.04	0.968	-.0128893	.0123729
shhlwl	-.006468	.0095563	-0.68	0.499	-.025198	.012262
shjobwl	.0002575	.007117	0.04	0.971	-.0136915	.0142066
shrelawl	-.0148903	.0065942	-2.26	0.024	-.0278146	-.001966
suprtwl	-.0041909	.0088489	-0.47	0.636	-.0215344	.0131526
suchrwl	.0319242	.0187143	1.71	0.088	-.0047551	.0686035
havmilsq	5.48e-07	1.88e-06	0.29	0.771	-3.14e-06	4.23e-06
_cons	3.542841	754.0254	0.00	0.996	-1474.32	1481.405

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	85	27	112
-	40	206	246
Total	125	233	358

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

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	68.00%
Specificity	$\Pr(- \sim D)$	88.41%
Positive predictive value	$\Pr(D +)$	75.89%
Negative predictive value	$\Pr(\sim D -)$	83.74%
False + rate for true ~D	$\Pr(+ \sim D)$	11.59%
False - rate for true D	$\Pr(- D)$	32.00%
False + rate for classified +	$\Pr(\sim D +)$	24.11%
False - rate for classified -	$\Pr(D -)$	16.26%
Correctly classified		81.28%

Logistic model for HP2hmcare, goodness-of-fit test

```

        number of observations =      358
    number of covariate patterns =      358
        Pearson chi2(306) =      314.35
            Prob > chi2 =      0.3590

```

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

Log-Lik Intercept Only:	-231.600	Log-Lik Full Model:	-149.920
D(304):	299.841	LR(51):	163.358
		Prob > LR:	0.000
McFadden's R2:	0.353	McFadden's Adj R2:	0.120
Maximum Likelihood R2:	0.366	Cragg & Uhler's R2:	0.505
McKelvey and Zavoina's R2:	0.599	Efron's R2:	0.401
Variance of y*:	8.211	Variance of error:	3.290
Count R2:	0.813	Adj Count R2:	0.464
AIC:	1.139	AIC*n:	407.841
BIC:	-1487.841	BIC':	136.549

```

453 .
454 . title4 "Partly trimmed Female Main effects model for dose=> homecare wave 1"
>

```

Partly trimmed Female Main effects model for dose=> homecare wave 1

```

455 .   logit hp2hmcare age radhlw1   ///
>       avgcumdosew1 bf4   if gender==2

```

```

Iteration 0:   log likelihood = -233.30573
Iteration 1:   log likelihood = -184.19159
Iteration 2:   log likelihood = -183.06271
Iteration 3:   log likelihood = -183.05768
Iteration 4:   log likelihood = -183.05768

```

Logistic regression	Number of obs	=	362
	LR chi2(4)	=	100.50
	Prob > chi2	=	0.0000
Log likelihood = -183.05768	Pseudo R2	=	0.2154

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0770328	.0130012	5.93	0.000	.0515508	.1025148
radhlw1	-.0011136	.0035739	-0.31	0.755	-.0081184	.0058911
avgcumdosew1	-.5567889	.2722015	-2.05	0.041	-1.090294	-.0232837
bf4	-.1227731	.0262991	-4.67	0.000	-.1743185	-.0712277
_cons	-3.173011	.7808961	-4.06	0.000	-4.703539	-1.642482

```

456 .
457 . title4 "Partly trimmed Female Main effects model for dose=> homecare wave 1
> "

```

Partly trimmed Female Main effects model for dose=> homecare wave 1

```

458 . logit hp2hmcare age avgcumdosew1 bf4 if gender==2

```

```

Iteration 0: log likelihood = -233.72859
Iteration 1: log likelihood = -184.31143
Iteration 2: log likelihood = -183.15831
Iteration 3: log likelihood = -183.15306
Iteration 4: log likelihood = -183.15306

```

Logistic regression	Number of obs	=	363
	LR chi2(3)	=	101.15
	Prob > chi2	=	0.0000
Log likelihood = -183.15306	Pseudo R2	=	0.2164

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0763754	.0127317	6.00	0.000	.0514218	.1013291
avgcumdosew1	-.5587715	.2733515	-2.04	0.041	-1.094531	-.0230124
bf4	-.122574	.0262798	-4.66	0.000	-.1740815	-.0710665
_cons	-3.204746	.777467	-4.12	0.000	-4.728553	-1.680939

```

459 .
460 .
461 .
462 . di as input "female trimmed model for dose-home care impact in wv 1wave 1: d
> ose not signif"
female trimmed model for dose-home care impact in wv 1wave 1: dose not signif

463 . 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

```

```

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

465 .
466 . scalar SigDoseHmcrFw1 = "yes"

467 . scalar MainEffhmcFw1= "age b4 avgcumdosew1"

468 . scalar list
MainEffhmcFw1 = age b4 avgcumdosew1
hmcrMedFw1 = age avgcumdosew1 bf4 bf4m
hmcrMedMw1 = age
MainEffhmcMw1 = age shjobw1
MainEffwkFw1 = age
MainEffwkMw1 = age
MainEffVactnMw1 = age radhlw1
VactnMedFw1 = age illw1 radhlw1
VactnMedMw1 = age
VacatnModFw1 = none
MainEffVactnFw1 = age radhlw1 bf7m
SigDoseVactnFw1 = no
VactnModMw1 = none
inthobMedFw1 = age bf4 illw1 bf4m
inthobMedMw1 = age
  inthobMw1 = age
InthbModFw1 = none
MainEffInthbFw1 = age radhlw1 bf4
SigDoseInthbFw1 = no
InthbModMw1 = none
MainEffInthbMw1 = age radhlw1 shfamw1
SigDoseInthbMw1 = no
MainEffMw1 = radhlw1 bf4 bf40
sxlifeMedMw1 = radhlw1
sxlifeMedFw1 = age illw1 radhlw1 bf4 bf4m
MainEffsxlifeFw1 = age bf4 bf4m
SigDoseSxlifeFw1 = no
SigDosesxlifeMw1 = no
MainEffsxlifeMw1 = age bf4 bf40
SigDosePrbfmhmMw1 = no
vactnModMw1 = none
SigDoseVactnMw1 = no
SxLifeModFw1 = no
sxlifeModFw1 = none
sxlifeModMw1 = none
MaineffhmcMw1 = age bf4 bf40
SigDoseMEhmcMw1 = no
PrbfmhmMedFw1 = age bf4
PrbfmhmMedMw1 = age
MainEffPrbfmhmFw1 = age radhlw1 bf4

```

```

MainEffPrbfmhmMw1 = age bf4
PrbfmhmModFw1 = none
PrbfmhmModMw1 = none
SigDosePrbfmhmFw1 = no
SigDosePrbfhmMw1 = no
MainEffPrbfhmMw1 = age bf4
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
MainEffPrbsocMw1 = age bf4m
SigdoseMw1 = no
ProbsocMedFw1 = age bf4
ProbsocMedMw1 = radhlw1
ProbsocModFw1 = none
SigDoseProbsocMw1 = no
hmcrmedMw1 = radhlw1
hmcrmedFw1 = age b4 b40
SigdosehmcrFw1 = no
MainEffProbSocFw1 = age radhlw1 avgcumdosew1 shrelaw1 bf4
SigDoseProbsocFw1 = yes
PrbsocModMw1 = shjobw1Xd1 shrelaw1Xd1
    WkhmcrMw1 = age b4
    WkModFw1 = ageXd1
hmcareMedFw1 = age illw1
hmcareMedMw1 = age
SigDosehmcrFw1 = no
    wkMedMw1 = bf40
hmcrModFw1 = none
SigDoseHmcrFw1 = yes
    WkMedMw1 = bf40
hmcrModMw1 = none
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
VactnMedMw2 = 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

```

469 .

470 . title4 "Fully trimmed Female Main effects model for dose=> homecare wave 1"

Fully trimmed Female Main effects model for dose=> homecare wave 1

```

471 .   logit hp2hmcare age radhlw1 occ1w1-occ8w1 inclw1-inc4w1 ///
>       avgcumdosew1 bf4   if gender==2

```

```

Iteration 0:   log likelihood = -233.30573
Iteration 1:   log likelihood = -177.44485
Iteration 2:   log likelihood = -175.62926
Iteration 3:   log likelihood = -175.62508
Iteration 4:   log likelihood = -175.62508

```

```

Logistic regression                                Number of obs   =          362
                                                    LR chi2(16)    =          115.36
                                                    Prob > chi2    =           0.0000
Log likelihood = -175.62508                        Pseudo R2      =           0.2472

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0961718	.0183122	5.25	0.000	.0602806	.132063
radhlw1	-.0009397	.0037872	-0.25	0.804	-.0083624	.006483
occ1w1	-1.536209	1.27581	-1.20	0.229	-4.036751	.9643328
occ2w1	-1.066639	1.306018	-0.82	0.414	-3.626387	1.493109
occ3w1	-.9187994	1.316697	-0.70	0.485	-3.499477	1.661879
occ4w1	-1.809667	1.369371	-1.32	0.186	-4.493584	.8742504
occ5w1	-2.474943	1.459934	-1.70	0.090	-5.336361	.3864749
occ6w1	-2.384731	1.550879	-1.54	0.124	-5.424399	.6549365
occ7w1	-.2736949	1.305569	-0.21	0.834	-2.832564	2.285174
occ8w1	-.4828664	1.289472	-0.37	0.708	-3.010185	2.044453
inclw1	1.237577	1.315563	0.94	0.347	-1.340878	3.816033
inc2w1	1.563876	1.263131	1.24	0.216	-.9118151	4.039568
inc3w1	1.858766	1.259322	1.48	0.140	-.6094602	4.326992
inc4w1	1.650938	1.369374	1.21	0.228	-1.032987	4.334862
avgcumdosew1	-.6169468	.2918407	-2.11	0.035	-1.188944	-.0449496
bf4	-.1423744	.0286191	-4.97	0.000	-.1984668	-.086282
_cons	-4.384177	1.11318	-3.94	0.000	-6.56597	-2.202384

```

472 .

```

```
473 . title4 "Super trimmed Female Main effects model for dose=> homecare wave 1"
```

```
Super trimmed Female Main effects model for dose=> homecare wave 1
```

```
474 . sw, pr(.1): logit hp2hmcare age radhlw1 occ1w1-occ8w1 inclw1-inc4w1 ///
>     avgcumdosew1 bf4 bf7 if gender==2
      begin with full model
```

```
p = 0.8548 >= 0.1000 removing occ7w1
p = 0.8444 >= 0.1000 removing radhlw1
p = 0.7229 >= 0.1000 removing occ8w1
p = 0.3325 >= 0.1000 removing occ3w1
p = 0.3694 >= 0.1000 removing occ2w1
p = 0.2150 >= 0.1000 removing inclw1
p = 0.2936 >= 0.1000 removing inc4w1
p = 0.2169 >= 0.1000 removing inc2w1
p = 0.2571 >= 0.1000 removing occ4w1
p = 0.1614 >= 0.1000 removing occ1w1
p = 0.2137 >= 0.1000 removing inc3w1
p = 0.2479 >= 0.1000 removing occ6w1
p = 0.1543 >= 0.1000 removing occ5w1
p = 0.1037 >= 0.1000 removing bf7
```

Logistic regression	Number of obs	=	362
	LR chi2(3)	=	100.40
	Prob > chi2	=	0.0000
Log likelihood = -183.1063	Pseudo R2	=	0.2152

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0762363	.0127384	5.98	0.000	.0512695	.1012031
bf4	-.1224238	.0262785	-4.66	0.000	-.1739286	-.0709189
avgcumdosew1	-.5588394	.2733844	-2.04	0.041	-1.094663	-.0230158
_cons	-3.198013	.7776298	-4.11	0.000	-4.72214	-1.673887

```

475 .
476 . cap gen radhlw1Xd1 = radhlw1*avgcumdosew1

477 .
478 .
479 . title4 "female main effect plus interaction model"

```

female main effect plus interaction model

```

480 . xi:logit hp2hmcare age  avgcumdosew1 bf4  ageXd1 bf4Xd1 if gender==2

```

```

Iteration 0:  log likelihood = -233.72859
Iteration 1:  log likelihood = -183.82966
Iteration 2:  log likelihood = -182.5885
Iteration 3:  log likelihood = -182.58185
Iteration 4:  log likelihood = -182.58185

```

Logistic regression	Number of obs	=	363
	LR chi2(5)	=	102.29
	Prob > chi2	=	0.0000
Log likelihood = -182.58185	Pseudo R2	=	0.2188

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0849926	.0157492	5.40	0.000	.0541247	.1158604
avgcumdosew1	1.600207	2.155971	0.74	0.458	-2.625418	5.825832
bf4	-.1093288	.034593	-3.16	0.002	-.1771298	-.0415278
ageXd1	-.0339202	.0371133	-0.91	0.361	-.1066609	.0388205
bf4Xd1	-.0454367	.0710033	-0.64	0.522	-.1846007	.0937273
_cons	-3.755837	.945655	-3.97	0.000	-5.609287	-1.902388

```

481 .
482 . * there are no significant moderators for female dose=hmcare relationship
483 . scalar hmcrModFw1 = "none"

```

```

484 .
485 .
486 .
487 . scalar SigdosehmcrFw1="no"

488 .
489 .
490 . scalar MainEffhmcrFw1 = "age bf4"

491 .
492 .
493 . scalar hmcrModFw1 = "none"

494 .
495 .
496 . title4 "Mediator relationships for home care are tested below"
      _____
      Mediator relationships for home care are tested below
      _____

497 . title4  "H1 pt 2 wave 1 Mediation of home care testing for males"
      _____
      H1 pt 2 wave 1 Mediation of home care testing for males
      _____

498 .
499 .
500 .
501 . correlate bf4 age if gender==1
      (obs=340)

```

	bf4	age
bf4	1.0000	
age	-0.4041	1.0000

```
502 .
503 . des bf4
```

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

```
504 .
505 . glm bf4 avgcumdosew1 if gender==1, fam(gauss) link(identity)
```

Iteration 0: log likelihood = **-1026.9659**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
Deviance	= 8366.946191	Scale parameter	=	24.75428
Pearson	= 8366.946191	(1/df) Deviance	=	24.75428
		(1/df) Pearson	=	24.75428
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
Log likelihood = -1026.965868		<u>AIC</u>	=	6.05274
		<u>BIC</u>	=	6396.763

bf4	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	-.1031788	.161925	-0.64	0.524	-.4205461	.2141884
_cons	12.54134	.2786337	45.01	0.000	11.99523	13.08746

```
506 . glm hp2hmcare bf4 if gender==1, fam(binomial) link(probit) irls scale(dev)
```

Iteration 1: deviance = **268.3422**
 Iteration 2: deviance = **265.0048**
 Iteration 3: deviance = **264.9272**
 Iteration 4: deviance = **264.9269**
 Iteration 5: deviance = **264.9269**

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 264.9268544	(1/df) Deviance	=	.7838073
Pearson	= 286.2423079	(1/df) Pearson	=	.8468707

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1705.257

hp2hmcare	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.1429587	.015032	-9.51	0.000	-.1724209	-.1134964
_cons	.7855991	.1813087	4.33	0.000	.4302406	1.140958

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

507 .
 508 .
 509 . glm age avgcumdosew1 if gender==1, fam(gauss) link(identity)

Iteration 0: log likelihood = -1331.608

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	148.5632
Deviance = 50214.37624	(1/df) Deviance	=	148.5632
Pearson = 50214.37624	(1/df) Pearson	=	148.5632

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]
 Log likelihood = -1331.607976
 AIC = 7.844753
 BIC = 48244.19

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
510 . 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      :  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) = 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.)

```
511 .
512 . scalar hmcrMedMw1 = "radhlw1"

513 .
514 .
515 . title4 "radhlw1 is a possible mediator for men of hmcare in wave 1"
```

```
radhlw1 is a possible mediator for men of hmcare in wave 1
```

```
516 . glm radhlw1 avgcumdosew1 if gender==1, fam(gaussian) link(identity)
```

```
Iteration 0: log likelihood = -1710.3417
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	1378.645
Deviance	= 465981.8893	(1/df) Deviance	=	1378.645
Pearson	= 465981.8893	(1/df) Pearson	=	1378.645

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

	<u>AIC</u>	=	10.0726
Log likelihood = -1710.341694	<u>BIC</u>	=	464011.7

radhlw1	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew1	2.398285	1.208412	1.98	0.047	.0298407	4.766729	
_cons	44.66477	2.079384	21.48	0.000	40.58925	48.74029	

```
517 . glm hp2hmcare radhlw1 if gender==1 , fam(binomial) irls scale(dev) link(prob > it)
```

```
Iteration 1: deviance = 330.2185
Iteration 2: deviance = 329.7978
Iteration 3: deviance = 329.7977
Iteration 4: deviance = 329.7977
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 329.797656	(1/df) Deviance	=	.9757327
Pearson	= 341.5925114	(1/df) Pearson	=	1.010629

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

	BIC	=	-1640.386
--	-----	---	-----------

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.008257	.0020717	3.99	0.000	.0041965	.0123175
_cons	-1.236257	.1340392	-9.22	0.000	-1.498968	-.9735446

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

```
518 .
519 . title4 "Testing possible female home care mediators for home care in wave 1"
```

Testing possible female home care mediators for home care in wave 1

```
520 .
521 . title4 "Test of age as possible female mediator in wave 1"
```

Test of age as possible female mediator in wave 1

```
522 . glm age avgcumdosew1 if gender==2, fam(gauss) link(identity)
```

Iteration 0: log likelihood = **-1406.325**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.455
Deviance = 49260.25928	(1/df) Deviance	=	136.455
Pearson = 49260.25928	(1/df) Pearson	=	136.455

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

	<u>AIC</u>	=	7.759366
Log likelihood = -1406.325011	<u>BIC</u>	=	47132.38

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```
523 . 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      :  MQL 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.)

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

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

```
525 .
```

```
526 .
```

```
527 . title4 "Test of b40 as female mediator of home care in wave 1"
```

```
Test of b40 as female mediator of home care in wave 1
```

```
528 . glm bf40 avgcumdosew1 if gender==2, fam(gauss) link(identity)
```

```
Iteration 0: log likelihood = -818.49948
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	5.351018
Deviance = 1931.717442	(1/df) Deviance	=	5.351018
Pearson = 1931.717442	(1/df) Pearson	=	5.351018

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

Log likelihood = -818.4994757	AIC	=	4.520658
	BIC	=	-196.162

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.4524905	.2213302	2.04	0.041	.0186913	.8862898
_cons	3.013471	.1423225	21.17	0.000	2.734524	3.292417

```
529 . 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 (IRLS EIM)	Residual df	=	361
	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 : $g(u) = \text{invnorm}(u)$	[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.)

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

b40 with age is a mediator for women

531 .

532 .

533 .

534 . title4 "bf4 Test of female mediation of home care in wave 1"

bf4 Test of female mediation of home care in wave 1

535 . glm bf4 avgcumdosew1 if gender==2, fam(gauss) link(identity)

Iteration 0: log likelihood = **-1109.0162**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.52082
Deviance = 9574.015672	(1/df) Deviance	=	26.52082
Pearson = 9574.015672	(1/df) Pearson	=	26.52082
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	6.121302
Log likelihood = -1109.016226	<u>BIC</u>	=	7446.136

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```
536 . 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      : MQL 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) = invnorm(u)   [Probit]
```

```
BIC                                     = -1717.763
```

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
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.)

```
537 . title4 "bf4 alone is a mediator for women"
```

```
bf4 alone is a mediator for women
```

```
538 .
```

```
539 .
```

```
540 . glm illw1 avgcumdosew1 if gender==2, fam(gauss) link(identity)
```

```
Iteration 0:  log likelihood = -259.70777
```

```
Generalized linear models          No. of obs      =       363
Optimization      : ML              Residual df    =       361
Deviance          = 88.89203958      Scale parameter = .2462383
Pearson           = 88.89203958      (1/df) Deviance = .2462383
                                      (1/df) Pearson  = .2462383
```

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

Log likelihood	= -259.7077741	<u>AIC</u>	= 1.441916
		<u>BIC</u>	= -2038.987

	OIM					
illwl	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosewl	.0655142	.0474789	1.38	0.168	-.0275426	.1585711
_cons	.1570822	.0305304	5.15	0.000	.0972436	.2169207

```
541 . glm hp2hmcare illw1 if gender==2, fam(binomial) link(probit) irls scale(dev)
```

```
Iteration 1:    deviance = 451.3594
Iteration 2:    deviance = 450.782
Iteration 3:    deviance = 450.7819
Iteration 4:    deviance = 450.7819
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 450.7819203	(1/df) Deviance	=	1.248703
Pearson = 362.4981549	(1/df) Pearson	=	1.00415

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

BIC = -1677.098

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illwl	.5711151	.1643397	3.48	0.001	.2490151	.8932151
_cons	-.5078804	.0821368	-6.18	0.000	-.6688655	-.3468953

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

```

542 .
543 .
544 . title4 "multivariate Test of female mediation of home care in wave 1"

```

multivariate Test of female mediation of home care in wave 1

```

545 . mvreg bf4 age bf40 = avgcumdosew1 if gender==2

```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.149837	0.0253	9.376729	0.0024
age	363	2	11.6814	0.0338	12.64139	0.0004
bf40	363	2	2.313227	0.0114	4.179627	0.0416

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.477832	-.5398375
_cons	10.99384	.3168463	34.70	0.000	10.37075	11.61694
age						
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.775898	6.171859
_cons	48.88157	.7187038	68.01	0.000	47.4682	50.29494
bf40						
avgcumdosew1	.4524905	.2213302	2.04	0.042	.017232	.887749
_cons	3.013471	.1423225	21.17	0.000	2.733585	3.293356

```

546 . 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		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
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.)

```
547 . title4 "When bf4 & age are together" ///
> "only age & b4 are a wave 1 mediators for women"
```

When bf4 & age are together

```
548 .
549 . glm radhlw1 avgcumdosew1 if gender==2, fam(gaussian) link(identity)
```

Iteration 0: log likelihood = -1821.9477

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	360
	Scale parameter	=	1385.301
Deviance = 498708.3025	(1/df) Deviance	=	1385.301
Pearson = 498708.3025	(1/df) Pearson	=	1385.301

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

Log likelihood = -1821.947718	<u>AIC</u>	=	10.07706
	<u>BIC</u>	=	496587.3

radhlw1	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	3.789972	3.562254	1.06	0.287	-3.191917	10.77186
_cons	55.44948	2.293757	24.17	0.000	50.9538	59.94516

```

Iteration 1:  deviance = 463.5751
Iteration 2:  deviance = 463.0208
Iteration 3:  deviance = 463.0207
Iteration 4:  deviance = 463.0207

Generalized linear models
Optimization   :  MQL Fisher scoring
                  (IRLS EIM)
Deviance       =  463.0207118
Pearson        =  361.7039664

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

No. of obs      = 362
Residual df     = 360
Scale parameter = 1
(1/df) Deviance = 1.286169
(1/df) Pearson  = 1.004733

[Bernoulli]
[Probit]

BIC = -1657.971

```

	EIM					
hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlwl	.0034921	.0020846	1.68	0.094	-.0005936	.0075779
_cons	-.5996677	.1437134	-4.17	0.000	-.8813409	-.3179945

```
551 .
552 . title "Test of female mediation of home care in wave 1"
```

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

```
553 . mvreg bf4 age bf40 illw1 = avgcumdosew1 if gender==2
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
bf4	363	2	5.149837	0.0253	9.376729	0.0024
age	363	2	11.6814	0.0338	12.64139	0.0004
bf40	363	2	2.313227	0.0114	4.179627	0.0416
illw1	363	2	.4962241	0.0052	1.904017	0.1685

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
bf4						
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.477832	-.5398375
_cons	10.99384	.3168463	34.70	0.000	10.37075	11.61694
age						
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.775898	6.171859
_cons	48.88157	.7187038	68.01	0.000	47.4682	50.29494
bf40						
avgcumdosew1	.4524905	.2213302	2.04	0.042	.017232	.887749
_cons	3.013471	.1423225	21.17	0.000	2.733585	3.293356
illw1						
avgcumdosew1	.0655142	.0474789	1.38	0.168	-.0278557	.1588841
_cons	.1570822	.0305304	5.15	0.000	.0970423	.217122

```
554 . glm hp2hmcare bf4 age bf40 illw1 if gender==2, fam(binomial) ///
> link(probit) irls scale(dev)
```

```
Iteration 1: deviance = 368.0172
Iteration 2: deviance = 367.5924
Iteration 3: deviance = 367.5922
Iteration 4: deviance = 367.5922
```

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	358
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 367.592256	(1/df) Deviance	=	1.026794
Pearson	= 388.4520039	(1/df) Pearson	=	1.085061

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

[Bernoulli]
 [Probit]

BIC = -1742.604

hp2hmcare	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.0651744	.01601	-4.07	0.000	-.0965533	-.0337954
age	.0411498	.007244	5.68	0.000	.0269518	.0553477
bf40	-.0137692	.0343692	-0.40	0.689	-.0811316	.0535933
illw1	.3518084	.15798	2.23	0.026	.0421733	.6614435
_cons	-1.887052	.4701989	-4.01	0.000	-2.808625	-.9654796

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

```

555 . qui: {
      When all are together only age and b4 are a wave 1 mediators for women

556 .
557 .
558 . scalar hmcrMedFw1 = "age bf4"

559 .
560 . scalar SigDosehmcrMw1 = "no"

561 . scalar MainEffhmcrMw1 = "age"

562 . scalar MainEffhmcrFw1 = "age"

563 . scalar hmcrmedFw1 = "age b4 b40"

564 . scalar hmcrmedMw1 = "radhlw1"

565 .
566 . scalar hmcareMedMw1 = "age "
```

```

567 . scalar hmcareMedFw1 = "age illw1"

568 . set more off

569 . scalar list
MainEffhmcrFw1 = age
MainEffhmcrMw1 = age
hmcrMedFw1 = age bf4
hmcrMedMw1 = radhlw1
MainEffwkFw1 = age
MainEffwkMw1 = age
MainEffVactnMw1 = age radhlw1
VactnMedFw1 = age illw1 radhlw1
VactnMedMw1 = age
VacatnModFw1 = none
MainEffVactnFw1 = age radhlw1 bf7m
SigDoseVactnFw1 = no
VactnModMw1 = none
inthobMedFw1 = age bf4 illw1 bf4m
inthobMedMw1 = age
  inthobMw1 = age
InthbModFw1 = none
MainEffInthbFw1 = age radhlw1 bf4
SigDoseInthbFw1 = no
InthbModMw1 = none
MainEffInthbMw1 = age radhlw1 shfamw1
SigDoseInthbMw1 = no
MainEffMw1 = radhlw1 bf4 bf40
sxlifeMedMw1 = radhlw1
sxlifeMedFw1 = age illw1 radhlw1 bf4 bf4m
MainEffsxlifeFw1 = age bf4 bf4m
SigDoseSxlifeFw1 = no
SigDosesxlifeMw1 = no
MainEffsxlifeMw1 = age bf4 bf40
SigDosePrbfmhmMw1 = no
vactnModMw1 = none
SigDoseVactnMw1 = no
SxLifeModFw1 = no
sxlifeModFw1 = none
sxlifeModMw1 = none
MaineffhmcrMw1 = age bf4 bf40
SigDoseMEhmcrW1 = no
PrbfmhmMedFw1 = age bf4
PrbfmhmMedMw1 = age
MainEffPrbfmhmFw1 = age radhlw1 bf4
MainEffPrbfmhmMw1 = age bf4
PrbfmhmModFw1 = none
PrbfmhmModMw1 = none
SigDosePrbfmhmFw1 = no

```

```

SigDosePrbfhmMw1 = no
MainEffPrbfhmMw1 = age bf4
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
MainEffPrbsocMw1 = age bf4m
SigdoseMw1 = no
ProbsocMedFw1 = age bf4
ProbsocMedMw1 = radhlw1
ProbsocModFw1 = none
SigDoseProbsocMw1 = no
hmcrmedMw1 = radhlw1
hmcrmedFw1 = age b4 b40
SigdosehmcrFw1 = no
MainEffProbSocFw1 = age radhlw1 avgcumdosew1 shrelaw1 bf4
SigDoseProbsocFw1 = yes
PrbsocModMw1 = shjobw1Xd1 shrelaw1Xd1
    WkhmcrMw1 = age b4
    WkModFw1 = ageXd1
hmcareMedFw1 = age illw1
hmcareMedMw1 = age
SigDosehmcrFw1 = no
    wkMedMw1 = bf40
hmcrModFw1 = none
SigDoseHmcrFw1 = yes
    WkMedMw1 = bf40
hmcrModMw1 = none
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
VactnMedMw2 = 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

```

```

570 .
571 . * conclusion "age & illw1 are main effects as possible male & female mediato
    > rs"
572 . * conclusion title "their interaction is not a mediator"
573 .
574 . title4 "2. summary matrix construction for H1 pt 2 wave 1 dose=>Home care im
    > pact"

```

```

2. summary matrix construction for H1 pt 2 wave 1 dose=>Home care impact

```

```

575 . set more off

576 . matrix define hmcMw1 = J(1,8, 0)

577 . matrix define hmcFw1 = J(1,8, 0)

578 . matrix colnames hmcMw1= hypnum ptnum wave gender medsig numMA sig numModsi
> g ///
> numMed

579 . matrix colnames hmcFw1= hypnum ptnum wave gender medsig numMA sig numModsi
> g ///
> numMed

580 . matrix rownames hmcMw1 = hmcareM

581 . matrix rownames hmcFw1 = hmcareF

582 . matrix define hmcMw1= (1, 2, 1, 1, 0 , 2, 0 , 1 )

583 . matrix define hmcFw1= (1, 2, 1, 2, 0 ,2, 0 , 2 )

584 . matrix define H1pt2w1 = ( wkMw1 \ wkFw1 \ hmcMw1 \ hmcFw1)

585 . matrix colnames H1pt2w1 = hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

586 . matrix colnames H1pt2w1 = hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

587 . matrix rownames H1pt2w1 = wkMw1 wkFw1 hmcMw1 hmcFw1

588 . matlist H1pt2w1

```

		hypnum	ptnum	wave	gender	medsig	numMA sig
> g	numModsig	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2	0	1					
	wkFw1	1	2	1	2	0	
> 1	1	2					
	hmcMw1	1	2	1	1	0	
> 2	0	1					
	hmcFw1	1	2	1	2	0	
> 2	0	2					

```

589 .
590 . * see scalar list for names of variables
591 . scalar list
MainEffhmcrFw1 = age
MainEffhmcrMw1 = age
hmcrMedFw1 = age bf4
hmcrMedMw1 = radhlw1
MainEffwkFw1 = age
MainEffwkMw1 = age
MainEffVactnMw1 = age radhlw1
VactnMedFw1 = age illw1 radhlw1
VactnMedMw1 = age
VacatnModFw1 = none
MainEffVactnFw1 = age radhlw1 bf7m
SigDoseVactnFw1 = no
VactnModMw1 = none
inthobMedFw1 = age bf4 illw1 bf4m
inthobMedMw1 = age
    inthobMw1 = age
InthbModFw1 = none
MainEffInthbFw1 = age radhlw1 bf4
SigDoseInthbFw1 = no
InthbModMw1 = none
MainEffInthbMw1 = age radhlw1 shfamw1
SigDoseInthbMw1 = no
MainEffMw1 = radhlw1 bf4 bf40
sxlifeMedMw1 = radhlw1
sxlifeMedFw1 = age illw1 radhlw1 bf4 bf4m
MainEffsxlifeFw1 = age bf4 bf4m
SigDoseSxlifeFw1 = no
SigDosesxlifeMw1 = no
MainEffsxlifeMw1 = age bf4 bf40
SigDosePrbfmhmMw1 = no
vactnModMw1 = none
SigDoseVactnMw1 = no
SxLifeModFw1 = no
sxlifeModFw1 = none
sxlifeModMw1 = none
MaineffhmcrMw1 = age bf4 bf40
SigDoseMEhmcrW1 = no
PrbfmhmMedFw1 = age bf4
PrbfmhmMedMw1 = age
MainEffPrbfmhmFw1 = age radhlw1 bf4
MainEffPrbfmhmMw1 = age bf4
PrbfmhmModFw1 = none
PrbfmhmModMw1 = none
SigDosePrbfmhmFw1 = no
SigDosePrbfhmMw1 = no
MainEffPrbfhmMw1 = age bf4

```

```

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
MainEffPrbsocMw1 = age bf4m
SigdoseMw1 = no
ProbsocMedFw1 = age bf4
ProbsocMedMw1 = radhlw1
ProbsocModFw1 = none
SigDoseProbsocMw1 = no
hmcrmedMw1 = radhlw1
hmcrmedFw1 = age b4 b40
SigdosehmcrFw1 = no
MainEffProbSocFw1 = age radhlw1 avgcumdosew1 shrelaw1 bf4
SigDoseProbsocFw1 = yes
PrbsocModMw1 = shjobw1Xd1 shrelaw1Xd1
    WkhmcrMw1 = age b4
    WkModFw1 = ageXd1
hmcareMedFw1 = age illw1
hmcareMedMw1 = age
SigDosehmcrFw1 = no
    wkMedMw1 = bf40
hmcrModFw1 = none
SigDoseHmcrFw1 = yes
    WkMedMw1 = bf40
hmcrModMw1 = none
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
    WkModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
VactnMedMw2 = 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

```

```

592 .
593 .
594 . * X * missing the number of main effects in the trimmed models
595 .
596 . //////////////////////////////////////
    > *----- Chunk 4   Dose social problem impact relationship HP2probsoc
597 .
598 .
599 . title "3.  H1 part 2 wave 1  Dose - HP2probsoc impact tested"

```



```

604 .
605 .      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 specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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= 1

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

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

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

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

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

note: occ6w1 != 0 predicts failure perfectly
 occ6w1 dropped and 5 obs not used

note: occ7w1 != 0 predicts failure perfectly
 occ7w1 dropped and 4 obs not used

note: marrw12 != 0 predicts failure perfectly
 marrw12 dropped and 4 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: marrw16 omitted because of collinearity

Logistic regression	Number of obs	=	288
	LR chi2(43)	=	122.03
	Prob > chi2	=	0.0000
Log likelihood = -56.842934	Pseudo R2	=	0.5177

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0932157	.0488397	1.91	0.056	-.0025083	.1889398
_Ieduc_2	-1.534787	1.373444	-1.12	0.264	-4.226687	1.157114
_Ieduc_3	-2.172657	.8355094	-2.60	0.009	-3.810226	-.5350887
_Ieduc_4	0	(omitted)				
_Ieduc_5	-1.97152	1.083493	-1.82	0.069	-4.095126	.1520862
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w1	.4116733	2.029299	0.20	0.839	-3.565679	4.389026
occ2w1	1.622509	2.037766	0.80	0.426	-2.371439	5.616456
occ3w1	1.707699	2.267987	0.75	0.451	-2.737474	6.152872
occ4w1	.8391363	2.160815	0.39	0.698	-3.395982	5.074255
occ5w1	.2067084	2.315894	0.09	0.929	-4.33236	4.745777
occ6w1	0	(omitted)				
occ7w1	0	(omitted)				
occ8w1	1.657954	2.464035	0.67	0.501	-3.171466	6.487374
marrw11	8.254014	1282.599	0.01	0.995	-2505.595	2522.103
marrw12	0	(omitted)				
marrw13	6.455541	1282.6	0.01	0.996	-2507.394	2520.305
marrw15	45.60071	8350.823	0.01	0.996	-16321.71	16412.91
marrw16	0	(omitted)				
inc1w1	-4.624348	2.584817	-1.79	0.074	-9.690496	.4418005
inc2w1	-1.315065	2.130506	-0.62	0.537	-5.490781	2.860651
inc3w1	-.8805899	2.024434	-0.43	0.664	-4.848408	3.087229
inc4w1	-3.930393	2.652434	-1.48	0.138	-9.129068	1.268283
radhlw1	-.003808	.0098127	-0.39	0.698	-.0230405	.0154246
havmil	.0037068	.0075299	0.49	0.623	-.0110516	.0184652
avgcumdosew1	.1390885	.1022549	1.36	0.174	-.0613275	.3395044
bf1	.0837527	.0660851	1.27	0.205	-.0457717	.2132771
bf4	-.1765285	.2854179	-0.62	0.536	-.7359372	.3828802
bf9	.0121714	.045033	0.27	0.787	-.0760915	.1004344
bf10	-.0731627	.0326403	-2.24	0.025	-.1371365	-.0091889
bf11	-.0133658	.0915598	-0.15	0.884	-.1928197	.1660881
bf4m	-.1819261	.2441274	-0.75	0.456	-.6604069	.2965547
bf15m	0	(omitted)				
bf20	-.0741254	.0559936	-1.32	0.186	-.1838707	.03562
bf22	.0002567	.0001585	1.62	0.105	-.000054	.0005673
bf30	-.0003312	.0005407	-0.61	0.540	-.0013911	.0007286
bf40	-.1589223	.268107	-0.59	0.553	-.6844023	.3665577
deaw1	.073587	.5137846	0.14	0.886	-.9334124	1.080586
dvcew1	-33.19213	8251.737	-0.00	0.997	-16206.3	16139.92
sepaw1	21.75582	8052.548	0.00	0.998	-15760.95	15804.46
accdw1	1.124538	1.440947	0.78	0.435	-1.699667	3.948743
movew1	.4856006	.9962789	0.49	0.626	-1.46707	2.438271
illw1	.1109162	.620821	0.18	0.858	-1.105871	1.327703
shfamw1	-.0009812	.0110299	-0.09	0.929	-.0225994	.020637

shhlw1	.0236901	.0186204	1.27	0.203	-.0128052	.0601853
shjobw1	.0162037	.0119225	1.36	0.174	-.0071639	.0395713
shrelaw1	-.0240964	.0119609	-2.01	0.044	-.0475394	-.0006534
suprtw1	.0381166	.0331693	1.15	0.250	-.026894	.1031273
suchrw1	-.0419264	.049205	-0.85	0.394	-.1383664	.0545135
havmilsq	-5.12e-06	.0000107	-0.48	0.632	-.0000261	.0000159
_cons	-6.454218	1282.606	-0.01	0.996	-2520.316	2507.407

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	26	6	32
-	15	241	256
Total	41	247	288

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	63.41%
Specificity	$\Pr(- \sim D)$	97.57%
Positive predictive value	$\Pr(D +)$	81.25%
Negative predictive value	$\Pr(\sim D -)$	94.14%
False + rate for true ~D	$\Pr(+ \sim D)$	2.43%
False - rate for true D	$\Pr(- D)$	36.59%
False + rate for classified +	$\Pr(\sim D +)$	18.75%
False - rate for classified -	$\Pr(D -)$	5.86%
Correctly classified		92.71%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	288
number of covariate patterns =	288
Pearson $\chi^2(244)$ =	239.99
Prob > χ^2 =	0.5605

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

Log-Lik Intercept Only:	-117.857	Log-Lik Full Model:	-56.843
D(235):	113.686	LR(43):	122.029
		Prob > LR:	0.000
McFadden's R2:	0.518	McFadden's Adj R2:	0.068
Maximum Likelihood R2:	0.345	Cragg & Uhler's R2:	0.618
McKelvey and Zavoina's R2:	0.804	Efron's R2:	0.535
Variance of y*:	16.818	Variance of error:	3.290
Count R2:	0.927	Adj Count R2:	0.488
AIC:	0.763	AIC*n:	219.686
BIC:	-1217.110	BIC':	121.479

Full main model for HP2probsoc for wave= 1

chunk 4 H1 test:Gender= 2 model Wave = 1 for HP2probsoc

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
 note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 11 obs not used

note: _Ieduc_8 omitted because of collinearity
 convergence not achieved

Logistic regression	Number of obs	=	347
	LR chi2(49)	=	174.17
	Prob > chi2	=	0.0000
Log likelihood = -92.74522	Pseudo R2	=	0.4843

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1339222	.0304099	4.40	0.000	.07432	.1935245
_Ieduc_2	-14.8519	3.844577	-3.86	0.000	-22.38714	-7.316671
_Ieduc_3	-15.07441	3.702435	-4.07	0.000	-22.33105	-7.817769
_Ieduc_4	-15.0354	3.71929	-4.04	0.000	-22.32507	-7.745721
_Ieduc_5	-15.31894	3.642287	-4.21	0.000	-22.45769	-8.180187
_Ieduc_6	-15.97033	3.721806	-4.29	0.000	-23.26493	-8.675722
_Ieduc_7	-14.57197	4.858518	-3.00	0.003	-24.09449	-5.049449
_Ieduc_8	0	(omitted)				
occ1w1	-2.855851	2.862357	-1.00	0.318	-8.465967	2.754266
occ2w1	-2.736414	2.877102	-0.95	0.342	-8.375431	2.902603
occ3w1	-3.494041	2.901139	-1.20	0.228	-9.180168	2.192087
occ4w1	-3.424951	2.969387	-1.15	0.249	-9.244843	2.394942
occ5w1	-4.951372	3.138113	-1.58	0.115	-11.10196	1.199216
occ6w1	-4.529022	3.152748	-1.44	0.151	-10.70829	1.650251
occ7w1	-2.040185	2.865556	-0.71	0.476	-7.656572	3.576202
occ8w1	-1.038951	3.012173	-0.34	0.730	-6.942703	4.8648
marrw11	-3.017556	2.506541	-1.20	0.229	-7.930285	1.895174
marrw12	-1.448781	2.689444	-0.54	0.590	-6.719994	3.822432
marrw13	-2.818836	2.317521	-1.22	0.224	-7.361093	1.723421

marrw15	-4.022412	2.774385	-1.45	0.147	-9.460106	1.415282
marrw16	-3.024951	2.89161	-1.05	0.296	-8.692402	2.6425
inclw1	1.652153	2.826464	0.58	0.559	-3.887614	7.191921
inc2w1	.7523029	2.773835	0.27	0.786	-4.684314	6.188919
inc3w1	.8186418	2.79302	0.29	0.769	-4.655577	6.29286
inc4w1	1.416767	2.932929	0.48	0.629	-4.331668	7.165203
radhlw1	.0078893	.0071763	1.10	0.272	-.0061759	.0219546
havmil	-.0016014	.0088347	-0.18	0.856	-.018917	.0157143
avgcumdosew1	.9064706	.4019796	2.26	0.024	.1186049	1.694336
bf1	.035394	.0349482	1.01	0.311	-.0331032	.1038912
bf4	-.3079106	.2679557	-1.15	0.251	-.8330942	.217273
bf9	-.0727705	.032505	-2.24	0.025	-.1364792	-.0090617
bf10	-.0269165	.0168597	-1.60	0.110	-.059961	.0061279
bf11	-.0076362	.0541236	-0.14	0.888	-.1137164	.0984441
bf4m	.0576549	.2545602	0.23	0.821	-.441274	.5565838
bf15m	0	(omitted)				
bf20	-.0388067	.0274447	-1.41	0.157	-.0925973	.0149838
bf22	.0001098	.0001019	1.08	0.281	-.0000899	.0003094
bf30	.0003325	.0003748	0.89	0.375	-.000402	.001067
bf40	-.1036356	.1492079	-0.69	0.487	-.3960777	.1888066
deaw1	-.1970026	.3234174	-0.61	0.542	-.830889	.4368837
dvcew1	1.249232	2.862648	0.44	0.663	-4.361455	6.859919
sepaw1	-.7111444	3.235109	-0.22	0.826	-7.051842	5.629553
accdw1	-.7069674	1.124581	-0.63	0.530	-2.911106	1.497171
movew1	.3733727	.7129786	0.52	0.601	-1.02404	1.770785
illw1	-.2000586	.4406407	-0.45	0.650	-1.063699	.6635813
shfamw1	-.014563	.009194	-1.58	0.113	-.0325829	.003457
shhlw1	-.0149441	.0130685	-1.14	0.253	-.0405578	.0106697
shjobw1	.0015703	.0091986	0.17	0.864	-.0164586	.0195992
shrelaw1	-.0082661	.0085598	-0.97	0.334	-.0250429	.0085107
suprtw1	.0056689	.0131922	0.43	0.667	-.0201873	.0315251
suchrw1	-.0127124	.0182568	-0.70	0.486	-.0484951	.0230702
havmilsq	-1.64e-06	.0000208	-0.08	0.937	-.0000424	.0000391
_cons	15.72467	.	.	.	.	.

Note: 1 failure and 1 success completely determined.
Warning: convergence not achieved

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	46	12	58
-	28	261	289
Total	74	273	347

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

Sensitivity	$\Pr(+ D)$	62.16%
Specificity	$\Pr(- \sim D)$	95.60%
Positive predictive value	$\Pr(D +)$	79.31%
Negative predictive value	$\Pr(\sim D -)$	90.31%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	4.40%
False - rate for true D	$\Pr(- D)$	37.84%
False + rate for classified +	$\Pr(\sim D +)$	20.69%
False - rate for classified -	$\Pr(D -)$	9.69%
Correctly classified		88.47%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	347
number of covariate patterns =	347
Pearson $\chi^2(296)$ =	277.13
Prob > χ^2 =	0.7779

Measures of Fit for logistic of HP2probsoc

Log-Lik Intercept Only:	-179.829	Log-Lik Full Model:	-92.745
D(294):	185.490	LR(49):	174.168
		Prob > LR:	0.000
McFadden's R2:	0.484	McFadden's Adj R2:	0.190
Maximum Likelihood R2:	0.395	Cragg & Uhler's R2:	0.612
McKelvey and Zavoina's R2:	0.757	Efron's R2:	0.511
Variance of y*:	13.536	Variance of error:	3.290
Count R2:	0.885	Adj Count R2:	0.459
AIC:	0.840	AIC*n:	291.490
BIC:	-1534.211	BIC':	112.449

```

606 .
607 . *-----Chunk 4 dose3 social problem impact-----no sig dose main effe
> ct--
608 . title4 "Male trimmed models of dose and HP2probsoc relationship in wave 1"

```

```

Male trimmed models of dose and HP2probsoc relationship in wave 1

```

```

609 . * male models
610 .         forvalues j=1/1 {
        2. set more off
        3. local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
        4. title4 "trimmed HP2probsoc main effects models wave 1 for H1 part 2 with
> dose ns"
        5. title4 "wave 1 dose HP2probsoc relationship but avgcumdosew`j': Dose not
> signif"
        6. sw, pr(.1): logit HP2probsoc age radhlw1 accdw`j' `w`j'bf' shjobw`j' ha
> vmilsq ///
>         avgcumdosew`j' shhlw`j' shrelaw`j' if gender==1
        7.                 estat class
        8.                 estat gof
        9.                 fitstat
       10. }

```

```

trimmed HP2probsoc main effects models wave 1 for H1 part 2 with dose ns

```

```

wave 1 dose HP2probsoc relationship but avgcumdosew1: Dose not signif

```

```

note: bf15m dropped because of estimability
note: o.bf15m dropped because of estimability
note: 21 obs. dropped because of estimability
begin with full model
p = 0.8569 >= 0.1000 removing accdw1
p = 0.8345 >= 0.1000 removing bf4
p = 0.6090 >= 0.1000 removing havmilsq
p = 0.5895 >= 0.1000 removing radhlw1
p = 0.6078 >= 0.1000 removing bf40
p = 0.5292 >= 0.1000 removing bf20
p = 0.7236 >= 0.1000 removing bf1
p = 0.3440 >= 0.1000 removing bf11
p = 0.3090 >= 0.1000 removing bf10
p = 0.2900 >= 0.1000 removing bf9
p = 0.3215 >= 0.1000 removing bf30
p = 0.2860 >= 0.1000 removing bf22
p = 0.1710 >= 0.1000 removing avgcumdosew1
p = 0.1317 >= 0.1000 removing shhlw1
p = 0.1690 >= 0.1000 removing shrelaw1
p = 0.1067 >= 0.1000 removing shjobw1

```

Logistic regression

Number of obs = 319

LR chi2(2) = 71.57

Prob > chi2 = 0.0000

Pseudo R2 = 0.2925

Log likelihood = -86.576328

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0381014	.0181494	2.10	0.036	.0025293	.0736736
bf4m	-.2064677	.0337163	-6.12	0.000	-.2725504	-.140385
_cons	-.2900951	1.272585	-0.23	0.820	-2.784316	2.204126

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	13	6	19
-	28	272	300
Total	41	278	319

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	31.71%
Specificity	$\Pr(- \sim D)$	97.84%
Positive predictive value	$\Pr(D +)$	68.42%
Negative predictive value	$\Pr(\sim D -)$	90.67%
False + rate for true ~D	$\Pr(+ \sim D)$	2.16%
False - rate for true D	$\Pr(- D)$	68.29%
False + rate for classified +	$\Pr(\sim D +)$	31.58%
False - rate for classified -	$\Pr(D -)$	9.33%
Correctly classified		89.34%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations = 319
number of covariate patterns = 220
Pearson chi2(217) = 200.09
Prob > chi2 = 0.7885

Log-Lik Intercept Only:	-122.361	Log-Lik Full Model:	-86.576
D(316):	173.153	LR(2):	71.569
		Prob > LR:	0.000
McFadden's R2:	0.292	McFadden's Adj R2:	0.268
Maximum Likelihood R2:	0.201	Cragg & Uhler's R2:	0.375
McKelvey and Zavoina's R2:	0.372	Efron's R2:	0.293
Variance of y*:	5.240	Variance of error:	3.290
Count R2:	0.893	Adj Count R2:	0.171
AIC:	0.562	AIC*n:	179.153
BIC:	-1648.648	BIC':	-60.039

Trimmed male main effects model

```
612 . forvalues j=1/1 {
      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 1
> *
*****
for H1 part 2 with dose ns
> *
*****
> *
*****
18 Jun 2012      18:14:47  ***
> *
*****
> *
*****
> *

```

```

title2: Wave `j` dose HP2work relationship but avgcumdosew1: Dose not signif
              Date and time: 18 Jun 2012    18:14:47
              Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2
              Stata data file: chwide16june2012.dta
> has 2382 variables and 703 observations

Wave `j` dose HP2work relationship but avgcumdosew1: Dose not signif

```

613 .

614 . logit HP2probsoc age radhlw1 bf4m if gender==1

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -98.286147
Iteration 2:  log likelihood = -88.284687
Iteration 3:  log likelihood = -87.790699
Iteration 4:  log likelihood = -87.789842
Iteration 5:  log likelihood = -87.789842

```

Logistic regression	Number of obs	=	340
	LR chi2(3)	=	74.73
	Prob > chi2	=	0.0000
Log likelihood = -87.789842	Pseudo R2	=	0.2985

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0408433	.0180763	2.26	0.024	.0054145	.0762722
radhlw1	.0025885	.0057387	0.45	0.652	-.0086592	.0138361
bf4m	-.1982136	.0358985	-5.52	0.000	-.2685733	-.1278538
_cons	-.7777696	1.352662	-0.57	0.565	-3.428938	1.873399

615 .


```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -96.957486
Iteration 2:  log likelihood =   -91.634
Iteration 3:  log likelihood = -90.570723
Iteration 4:  log likelihood = -90.307985
Iteration 5:  log likelihood = -90.296231
Iteration 6:  log likelihood = -90.296206
Iteration 7:  log likelihood = -90.296206

```

Logistic regression

```

Number of obs   =      340
LR chi2(8)      =      69.71
Prob > chi2     =      0.0000
Pseudo R2      =      0.2785

```

Log likelihood = **-90.296206**

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0348678	.0289544	1.20	0.229	-.0218818	.0916174
avgcumdosew1	-13.34838	6.796946	-1.96	0.050	-26.67015	-.0266126
radhlw1	.0078565	.0063701	1.23	0.217	-.0046287	.0203416
shjobw1	.0100379	.010521	0.95	0.340	-.0105828	.0306587
ageXd1	.1331427	.1074383	1.24	0.215	-.0774326	.3437179
radhlw1Xd1	.0060028	.0144906	0.41	0.679	-.0223983	.0344039
shjobw1Xd1	.0795578	.0390013	2.04	0.041	.0031166	.155999
shrelaw1Xd1	-.0381989	.015358	-2.49	0.013	-.0683	-.0080977
_cons	-4.518141	1.78078	-2.54	0.011	-8.008406	-1.027877

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	10	3	13
-	31	296	327
Total	41	299	340

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

Sensitivity	$\Pr(+ D)$	24.39%
Specificity	$\Pr(- \sim D)$	99.00%
Positive predictive value	$\Pr(D +)$	76.92%
Negative predictive value	$\Pr(\sim D -)$	90.52%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.00%
False - rate for true D	$\Pr(- D)$	75.61%
False + rate for classified +	$\Pr(\sim D +)$	23.08%
False - rate for classified -	$\Pr(D -)$	9.48%
Correctly classified		90.00%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations = **340**
 number of covariate patterns = **331**
 Pearson $\chi^2(322)$ = **260.41**
 Prob > χ^2 = **0.9950**

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-90.296
D(331):	180.592	LR(8):	69.712
		Prob > LR:	0.000
McFadden's R2:	0.279	McFadden's Adj R2:	0.207
Maximum Likelihood R2:	0.185	Cragg & Uhler's R2:	0.356
McKelvey and Zavoina's R2:	0.588	Efron's R2:	0.248
Variance of y*:	7.976	Variance of error:	3.290
Count R2:	0.900	Adj Count R2:	0.171
AIC:	0.584	AIC*n:	198.592
BIC:	-1748.789	BIC':	-23.081

```

626 .
627 . title4 "male wave 1 moderators of dose and hmcare"

```

male wave 1 moderators of dose and hmcare

```

628 . scalar PrbsocModMw1 = "shjobw1Xd1 shrelaw1Xd1"

629 .
630 . forvalues j=1/1 {
      2. set more off
      3.  logit HP2probsoc age  radhlw1 shjobw`j' shrelaw1 ///
>      avgcumdosew`j'  shrelaw`j'Xd1 ///
>      shjobw1Xd1 if gender==1
      4.                                estat class
      5.                                estat gof
      6.                                fitstat
      7. }

```

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -98.199364
Iteration 2:  log likelihood = -91.871369
Iteration 3:  log likelihood = -91.382931
Iteration 4:  log likelihood = -91.279919
Iteration 5:  log likelihood = -91.277661
Iteration 6:  log likelihood = -91.277658

```

Logistic regression	Number of obs	=	340
	LR chi2(7)	=	67.75
	Prob > chi2	=	0.0000
Log likelihood = -91.277658	Pseudo R2	=	0.2707

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.065245	.0168011	3.88	0.000	.0323155	.0981744
radhlw1	.0097595	.0055022	1.77	0.076	-.0010247	.0205437
shjobw1	.0098453	.0120807	0.81	0.415	-.0138324	.033523
shrelaw1	.0002189	.0069348	0.03	0.975	-.0133731	.0138109
avgcumdosew1	-5.108591	3.138225	-1.63	0.104	-11.2594	1.042216
shrelaw1Xd1	-.0269782	.0164348	-1.64	0.101	-.0591898	.0052334
shjobw1Xd1	.0726131	.0410722	1.77	0.077	-.0078869	.1531132
_cons	-6.378223	1.306394	-4.88	0.000	-8.938707	-3.817739

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	9	4	13
-	32	295	327
Total	41	299	340

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	21.95%
Specificity	$\Pr(- \sim D)$	98.66%
Positive predictive value	$\Pr(D +)$	69.23%
Negative predictive value	$\Pr(\sim D -)$	90.21%
False + rate for true ~D	$\Pr(+ \sim D)$	1.34%
False - rate for true D	$\Pr(- D)$	78.05%
False + rate for classified +	$\Pr(\sim D +)$	30.77%
False - rate for classified -	$\Pr(D -)$	9.79%
Correctly classified		89.41%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    331
    Pearson chi2(323) =    280.63
        Prob > chi2 =    0.9572

```

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-91.278
D(332):	182.555	LR(7):	67.750
		Prob > LR:	0.000
McFadden's R2:	0.271	McFadden's Adj R2:	0.207
Maximum Likelihood R2:	0.181	Cragg & Uhler's R2:	0.347
McKelvey and Zavoina's R2:	0.590	Efron's R2:	0.242
Variance of y*:	8.026	Variance of error:	3.290
Count R2:	0.894	Adj Count R2:	0.122
AIC:	0.584	AIC*n:	198.555
BIC:	-1752.655	BIC':	-26.947

```

631 . scalar SigDoseProbsocMw1 = "no"

632 . * xx no signific radhlw13 by dose effect
633 . * xx for males no signif dose social problem effect
634 . * xx for males no significant moderator in dose social problem effect
635 .
636 . * female models
637 .
638 .
639 .
640 .
641 .
642 . title4 "H1 pt2 wave 1 trimmed female moderator model with basis functions"

```

```

H1 pt2 wave 1 trimmed female moderator model with basis functions

```

```

643 . forvalues j=1/1 {
      2. set more off
      3. local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40
      4. title "trimmed HP2probsoc main effects models wave 1 for H1 part 2 " "Dos
> e is signif Females"
      5. title "wave 1 dose HP2probsoc relationship but avgcumdosew`j': Dose signi
> f"
      6. sw, pr(.1): logit HP2probsoc age radhlw1 illw`j' `w1bf' ////
> shrelaw`j' avgcumdosew`j' if gender==2
      7.          estat class
      8.          estat gof
      9.          fitstat
     10. }

*****
> *
*****
> *
*****
> *
*****
> *
*****      trimmed HP2probsoc main effects models wave 1 for H1 part 2      ****
> *
*****      Dose is signif Females      ****
> *
*****
> *
*****
> *
*****
*****
18 Jun 2012      18:14:51      ****

```

```

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

*****
> *
*****
> *
*****
> *
***** wave 1 dose HP2probsoc relationship but avgcumdosew1: Dose signif ****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *

```

```

note: bf15m dropped because of estimability
note: o.bf15m dropped because of estimability
note: 11 obs. dropped because of estimability
begin with full model

```

```

p = 0.5688 >= 0.1000 removing illw1
p = 0.4993 >= 0.1000 removing bf40
p = 0.5410 >= 0.1000 removing bf22
p = 0.4121 >= 0.1000 removing bf11
p = 0.4390 >= 0.1000 removing bf10
p = 0.2876 >= 0.1000 removing bf1
p = 0.4202 >= 0.1000 removing bf20
p = 0.3289 >= 0.1000 removing bf30
p = 0.2425 >= 0.1000 removing bf9
p = 0.1125 >= 0.1000 removing bf4m

```

Logistic regression

Number of obs = 351

LR chi2(5) = 134.88

Prob > chi2 = 0.0000

Log likelihood = -113.34071

Pseudo R2 = 0.3731

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0966615	.0183518	5.27	0.000	.0606925	.1326304
radhlw1	.0116609	.004855	2.40	0.016	.0021453	.0211765
avgcumdosew1	.6600342	.2959902	2.23	0.026	.0799041	1.240164
shrelaw1	-.0108373	.005085	-2.13	0.033	-.0208036	-.0008709
bf4	-.1838833	.0354969	-5.18	0.000	-.2534559	-.1143107
_cons	-5.736784	1.146357	-5.00	0.000	-7.983602	-3.489965

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	41	14	55
-	33	263	296
Total	74	277	351

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	55.41%
Specificity	$\Pr(- \sim D)$	94.95%
Positive predictive value	$\Pr(D +)$	74.55%
Negative predictive value	$\Pr(\sim D -)$	88.85%

False + rate for true ~D	$\Pr(+ \sim D)$	5.05%
False - rate for true D	$\Pr(- D)$	44.59%
False + rate for classified +	$\Pr(\sim D +)$	25.45%
False - rate for classified -	$\Pr(D -)$	11.15%

Correctly classified	86.61%
----------------------	--------

Logistic model for HP2probsoc, goodness-of-fit test

```

        number of observations =      351
number of covariate patterns =      350
        Pearson chi2(344) =      376.81
        Prob > chi2 =      0.1078

```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-180.782	Log-Lik Full Model:	-113.341
D(345):	226.681	LR(5):	134.883
		Prob > LR:	0.000
McFadden's R2:	0.373	McFadden's Adj R2:	0.340
Maximum Likelihood R2:	0.319	Cragg & Uhler's R2:	0.496
McKelvey and Zavoina's R2:	0.548	Efron's R2:	0.411
Variance of y*:	7.277	Variance of error:	3.290
Count R2:	0.866	Adj Count R2:	0.365
AIC:	0.680	AIC*n:	238.681
BIC:	-1795.290	BIC':	-105.579

```

644 .
645 .
646 . scalar SigDoseProbsocFw1 = "yes"

647 . scalar MainEffProbSocFw1 = "age radhlw1 avgcumdosew1 shrelaw1 bf4"

648 .
649 . foreach var in b4 shrelaw1 {
      2. cap gen `var'Xd1 = `var'*avgcumdosew1
      3. }

650 .
651 . * testing the female moderator model with basis functions
652 . forvalues j=1/1 {
      2. set more off
      3. local w1bf bf1 bf4 bf9 bf10 bf11 bf14 bf15m bf20 bf22 bf30 bf40
      4. title "trimmed HP2socprob main effects  wv 1 for Hyp1 pt 2" "dose is sign
> if for females"
      5. title "wave 1 dose HP2socprob relationship but avgcumdosew`j'" " Dose is
> signif for females"
      6. sw, pr(.1): logit HP2probsoc age radhlw1 illw`j' `w1bf' ///
> shrelaw`j' avgcumdosew`j' bf4Xd1 shrelaw1Xd1 ///
> if gender==2
      7. estat class
      8. estat gof
      9. fitstat
     10. }

```


note: bf15m dropped because of estimability
note: o.bf15m dropped because of estimability
note: 11 obs. dropped because of estimability

begin with full model
p = **0.8198** >= 0.1000 removing **shrelaw1Xd1**
p = **0.4967** >= 0.1000 removing **illw1**
p = **0.4970** >= 0.1000 removing **bf14**
p = **0.4352** >= 0.1000 removing **bf1**
p = **0.4028** >= 0.1000 removing **bf11**
p = **0.3720** >= 0.1000 removing **bf10**
p = **0.3228** >= 0.1000 removing **bf20**
p = **0.3123** >= 0.1000 removing **bf30**
p = **0.2761** >= 0.1000 removing **bf9**
p = **0.1462** >= 0.1000 removing **bf4Xd1**
p = **0.1528** >= 0.1000 removing **bf40**
p = **0.3685** >= 0.1000 removing **bf22**

Logistic regression	Number of obs	=	351
	LR chi2(5)	=	134.88
	Prob > chi2	=	0.0000
Log likelihood = -113.34071	Pseudo R2	=	0.3731

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0966615	.0183518	5.27	0.000	.0606925	.1326304
radhlw1	.0116609	.004855	2.40	0.016	.0021453	.0211765
avgcumdosew1	.6600342	.2959902	2.23	0.026	.0799041	1.240164
shrelaw1	-.0108373	.005085	-2.13	0.033	-.0208036	-.0008709
bf4	-.1838833	.0354969	-5.18	0.000	-.2534559	-.1143107
_cons	-5.736784	1.146357	-5.00	0.000	-7.983602	-3.489965

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	41	14	55
-	33	263	296
Total	74	277	351

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

Sensitivity	$\Pr(+ D)$	55.41%
Specificity	$\Pr(- \sim D)$	94.95%
Positive predictive value	$\Pr(D +)$	74.55%
Negative predictive value	$\Pr(\sim D -)$	88.85%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.05%
False - rate for true D	$\Pr(- D)$	44.59%
False + rate for classified +	$\Pr(\sim D +)$	25.45%
False - rate for classified -	$\Pr(D -)$	11.15%
Correctly classified		86.61%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations = **351**
 number of covariate patterns = **350**
 Pearson $\chi^2(344)$ = **376.81**
 Prob > χ^2 = **0.1078**

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-180.782	Log-Lik Full Model:	-113.341
D(345):	226.681	LR(5):	134.883
		Prob > LR:	0.000
McFadden's R2:	0.373	McFadden's Adj R2:	0.340
Maximum Likelihood R2:	0.319	Cragg & Uhler's R2:	0.496
McKelvey and Zavoina's R2:	0.548	Efron's R2:	0.411
Variance of y*:	7.277	Variance of error:	3.290
Count R2:	0.866	Adj Count R2:	0.365
AIC:	0.680	AIC*n:	238.681
BIC:	-1795.290	BIC':	-105.579

```

653 .
654 . scalar ProbsocModFw1 = "none"

655 .
656 .
657 . title4 "H1 pt 2 wave 1 testing for mediators for males"

```

H1 pt 2 wave 1 testing for mediators for males

```

658 . * Male mediator dose social problem response models
659 .
660 .
661 .
662 .
663 . glm age avgcumdosew1 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1331.608**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	148.5632
Deviance = 50214.37624	(1/df) Deviance	=	148.5632
Pearson = 50214.37624	(1/df) Pearson	=	148.5632

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

Log likelihood = -1331.607976	<u>AIC</u>	=	7.844753
	<u>BIC</u>	=	48244.19

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
664 . 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      :  MQL 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.)

```
665 .
```

```
666 . glm radhlw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1710.3417
```

```
Generalized linear models                      No. of obs      =       340
Optimization      :  ML                      Residual df     =       338
Deviance          = 465981.8893              Scale parameter = 1378.645
Pearson           = 465981.8893              (1/df) Deviance = 1378.645
                                          (1/df) Pearson  = 1378.645
```

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

Log likelihood    = -1710.341694              AIC              = 10.0726
                                          BIC              = 464011.7
```

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	2.398285	1.208412	1.98	0.047	.0298407	4.766729
_cons	44.66477	2.079384	21.48	0.000	40.58925	48.74029

```
667 . glm HP2probsoc radhlw1 if gender==1,fam(bin) irls link(probit) scale(dev)
```

```
Iteration 1:  deviance = 234.6563
Iteration 2:  deviance = 229.8984
Iteration 3:  deviance = 229.7634
Iteration 4:  deviance = 229.7633
Iteration 5:  deviance = 229.7633
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 229.7632837	(1/df) Deviance	=	.679773
Pearson = 344.9083225	(1/df) Pearson	=	1.020439

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

```
BIC = -1740.42
```

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.0108869	.0020577	5.29	0.000	.0068539	.0149198
_cons	-1.765962	.1445027	-12.22	0.000	-2.049182	-1.482742

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

```
668 .
```

```
669 . glm shjobw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1710.378
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1378.939
Deviance = 466081.3297	(1/df) Deviance	=	1378.939
Pearson = 466081.3297	(1/df) Pearson	=	1378.939

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

	AIC	=	10.07281
Log likelihood = -1710.377969	BIC	=	464111.1

shjobw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	1.461274	1.208541	1.21	0.227	-.907423	3.82997
_cons	48.94341	2.079606	23.53	0.000	44.86746	53.01936

```
670 . glm HP2probsoc shjobw1 if gender==1,fam(bin) irls link(probit) scale(dev)
```

```
Iteration 1: deviance = 227.0059
Iteration 2: deviance = 218.5961
Iteration 3: deviance = 218.011
Iteration 4: deviance = 218.0073
Iteration 5: deviance = 218.0072
Iteration 6: deviance = 218.0072
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 218.0072484	(1/df) Deviance	=	.6449919
Pearson = 380.0066656	(1/df) Pearson	=	1.12428

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

BIC	=	-1752.176
-----	---	-----------

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw1	.0149051	.0023429	6.36	0.000	.010313	.0194971
_cons	-2.086099	.1780182	-11.72	0.000	-2.435009	-1.73719

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

671 .

672 . glm shrelaw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1715.4166

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1420.421
Deviance = 480102.3567	(1/df) Deviance	=	1420.421
Pearson = 480102.3567	(1/df) Pearson	=	1420.421
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	AIC	=	10.10245
Log likelihood = -1715.416629	BIC	=	478132.2

shrelaw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.0649405	1.226584	-0.05	0.958	-2.469002	2.339121
_cons	29.57199	2.110654	14.01	0.000	25.43518	33.7088

673 . glm HP2probsoc shrelaw1 if gender==1,fam(bin) irls link(probit) scale(dev)

Iteration 1: deviance = 250.4419
Iteration 2: deviance = 249.8324
Iteration 3: deviance = 249.8314
Iteration 4: deviance = 249.8314

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 249.8314263	(1/df) Deviance	=	.7391462
Pearson = 340.1867245	(1/df) Pearson	=	1.00647

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1720.352

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw1	.0015698	.0019726	0.80	0.426	-.0022964	.0054361
_cons	-1.220468	.0980174	-12.45	0.000	-1.412578	-1.028357

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

674 .
 675 . title4 "Shjobw1 can be a mediator with others"

Shjobw1 can be a mediator with others

676 . glm radhlw1 shjobw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1679.4377

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	1152.894
Deviance = 388525.4251	(1/df) Deviance	=	1152.894
Pearson = 388525.4251	(1/df) Pearson	=	1152.894

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

	<u>AIC</u>	=	9.896692
Log likelihood = -1679.437708	<u>BIC</u>	=	386561.1

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw1	.4076599	.0497352	8.20	0.000	.3101807	.5051391
avgcumdosew1	1.802582	1.107442	1.63	0.104	-.3679637	3.973128
_cons	24.71251	3.088883	8.00	0.000	18.65841	30.76661

```

677 . glm HP2probsoc shjobw1 avgcumdosew1 shjobw1Xd1 radhlw1 if gender==1,fam(bin)
> ///
> irls scale(dev) link(probit)

```

```

Iteration 1:  deviance = 219.4001
Iteration 2:  deviance = 209.1683
Iteration 3:  deviance = 208.2026
Iteration 4:  deviance = 208.1798
Iteration 5:  deviance = 208.1796
Iteration 6:  deviance = 208.1796
Iteration 7:  deviance = 208.1796

```

```

Generalized linear models                                No. of obs      =       340
Optimization      :  ML Fisher scoring                 Residual df     =       335
                   (IRLS EIM)                          Scale parameter =         1
Deviance          =   208.179583                       (1/df) Deviance =   .6214316
Pearson           =   348.7623267                       (1/df) Pearson  =   1.041082

```

```

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

```

```

BIC = -1744.517

```

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
shjobw1	.0101989	.0030577	3.34	0.001	.004206	.0161918
avgcumdosew1	-.5046729	.500832	-1.01	0.314	-1.486286	.4769398
shjobw1Xd1	.0071158	.0061813	1.15	0.250	-.0049993	.0192309
radhlw1	.0070111	.0022234	3.15	0.002	.0026533	.0113688
_cons	-2.183344	.2368622	-9.22	0.000	-2.647586	-1.719103

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

```

678 .
679 . scalar ProbsocMedMw1 = "radhlw1"

```

```

680 .
681 . title4 "H1 pt2 wave 1 HP2probsoc female mediator tests"

```

H1 pt2 wave 1 HP2probsoc female mediator tests

```

682 .
683 . // age is a possible female mediator
684 . glm age avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.325**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.455
Deviance = 49260.25928	(1/df) Deviance	=	136.455
Pearson = 49260.25928	(1/df) Pearson	=	136.455

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

	<u>AIC</u>	=	7.759366
Log likelihood = -1406.325011	<u>BIC</u>	=	47132.38

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```

685 . glm HP2probsoc age if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **289.3253**
 Iteration 2: deviance = **280.9528**
 Iteration 3: deviance = **280.5176**
 Iteration 4: deviance = **280.5162**
 Iteration 5: deviance = **280.5162**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 280.5161869	(1/df) Deviance	=	.7770531
Pearson = 406.2926804	(1/df) Pearson	=	1.125464

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

BIC = -1847.363

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0683554	.007474	9.15	0.000	.0537067	.083004
_cons	-4.505136	.424587	-10.61	0.000	-5.337311	-3.672961

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

```

686 .
687 . // radhlw1 is a possible female mediator
688 . glm radhlw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = -1821.9477

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	360
	Scale parameter	=	1385.301
Deviance = 498708.3025	(1/df) Deviance	=	1385.301
Pearson = 498708.3025	(1/df) Pearson	=	1385.301

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

	<u>AIC</u>	=	10.07706
Log likelihood = -1821.947718	<u>BIC</u>	=	496587.3

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.789972	3.562254	1.06	0.287	-3.191917	10.77186
_cons	55.44948	2.293757	24.17	0.000	50.9538	59.94516

```
689 . glm HP2probsoc radhlw1 if gender==2,fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 347.1581
Iteration 2:  deviance = 346.2367
Iteration 3:  deviance = 346.2357
Iteration 4:  deviance = 346.2357
```

Generalized linear models	No. of obs	=	362
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 346.2357277	(1/df) Deviance	=	.9617659
Pearson = 365.2532496	(1/df) Pearson	=	1.014592

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

```
BIC = -1774.756
```

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.0094598	.0021222	4.46	0.000	.0053004	.0136191
_cons	-1.413461	.1575297	-8.97	0.000	-1.722213	-1.104708

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

```
690 .
691 . // bf4 is a possible female mediator
692 . glm bf4 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1109.0162
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.52082
Deviance = 9574.015672	(1/df) Deviance	=	26.52082
Pearson = 9574.015672	(1/df) Pearson	=	26.52082

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

	<u>AIC</u>	=	6.121302
Log likelihood = -1109.016226	<u>BIC</u>	=	7446.136

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```
693 . 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.)

694 .

695 . glm shrelaw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1801.2674**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1202.293
Deviance = 434027.9437	(1/df) Deviance	=	1202.293
Pearson = 434027.9437	(1/df) Pearson	=	1202.293
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.935358
Log likelihood = -1801.267425	<u>BIC</u>	=	431900.1

shrelaw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	5.240218	3.317628	1.58	0.114	-1.262215	11.74265
_cons	26.01592	2.133342	12.19	0.000	21.83464	30.19719

696 . glm HP2probsoc shrelaw1 if gender==2,fam(bin) irls scale(dev) link(probit)

Iteration 1: deviance = **367.3685**
 Iteration 2: deviance = **367.117**
 Iteration 3: deviance = **367.117**
 Iteration 4: deviance = **367.117**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 367.1169775	(1/df) Deviance	=	1.016945
Pearson = 362.9967567	(1/df) Pearson	=	1.005531
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	<u>BIC</u>	=	-1760.762

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw1	-.0003307	.0021782	-0.15	0.879	-.0045998	.0039385
_cons	-.8187957	.0962545	-8.51	0.000	-1.007451	-.6301402

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

```

697 .
698 .
699 . glm radhlw1 shjobw1 avgcumdosew1 shjobw1Xd1 if gender==2, fam(gaus) link(ide
> ntity)

```

Iteration 0: log likelihood = -1821.765

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	358
	Scale parameter	=	1391.635
Deviance = 498205.2021	(1/df) Deviance	=	1391.635
Pearson = 498205.2021	(1/df) Pearson	=	1391.635

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

	AIC	=	10.0871
Log likelihood = -1821.765032	BIC	=	496096

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw1	.0182877	.0685464	0.27	0.790	-.1160606	.1526361
avgcumdosew1	12.32024	14.83908	0.83	0.406	-16.76382	41.4043
shjobw1Xd1	-.1018921	.1735559	-0.59	0.557	-.4420555	.2382713
_cons	53.68631	4.758015	11.28	0.000	44.36077	63.01185

```

700 . glm HP2probsoc shjobw1 avgcumdosew1 shjobw1Xd1 if gender==2,fam(bin) irls s
    > cale(dev) link(probit)

```

```

Iteration 1:  deviance =  341.3502
Iteration 2:  deviance =  340.0594
Iteration 3:  deviance =  340.039
Iteration 4:  deviance =  340.0389
Iteration 5:  deviance =  340.0389

```

```

Generalized linear models                                No. of obs      =       363
Optimization      :  ML Fisher scoring                 Residual df     =       359
                   ( IRLS EIM )                       Scale parameter =         1
Deviance          =  340.0389343                        (1/df) Deviance =  .9471837
Pearson           =  349.6343388                        (1/df) Pearson  =  .9739118

```

```

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

```

```

BIC = -1776.052

```

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
shjobw1	.0078885	.0028001	2.82	0.005	.0024004	.0133767
avgcumdosew1	2.042963	.654931	3.12	0.002	.7593215	3.326604
shjobw1Xd1	-.0171602	.00714	-2.40	0.016	-.0311544	-.0031661
_cons	-1.586799	.2154854	-7.36	0.000	-2.009142	-1.164455

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

```

701 .
702 .
703 . scalar SigDoseProbsocFw1 = "yes"
704 . scalar SigDoseProbsocMw1 = "no"

```

```

705 .
706 .
707 . scalar MainEffPrbsocMw1 = "age bf4m"

708 . scalar MainEffProbSocFw1 = "age radhlw1 avgcumdosew1 shrelaw1 bf4"

709 .
710 . scalar PrbsocModMw1 = "shjobw1Xd1 shrelaw1Xd1"

711 . scalar ProbsocModFw1 = "none"

712 .
713 .
714 . scalar ProbsocMedMw1 = "radhlw1"

715 . scalar ProbsocMedFw1 = "age bf4 "

716 .
717 .
718 . * male hp2spM w1 mediators: age
719 . * dose is not significant main effect for males
720 . * female hp2spF w1 mediators: age radhlw1
721 . * dose is not sig main effect for males
722 .
723 .
724 .
725 .
726 .
727 . title4 "3. Matrix summary for H1 pt2 wave 1 HP2probsoc Impact"

```

```

3. Matrix summary for H1 pt2 wave 1 HP2probsoc Impact

```

```

728 .      matrix define  spMw1 = J(1,8, 0)

729 .      matrix define  spFw1 = J(1,8, 0)

```

```

730 . matrix colnames  spMw1=  hypnum ptnum wave gender medsig numMASig numModsig
> numMed

731 . matrix colnames  spFw1=  hypnum ptnum wave gender medsig numMASig numModsig
> numMed

732 .
733 .      matrix define  spMw1= (1, 2, 1, 1, 1, 2, 2, 1 )
734 .      matrix define  spFw1= (1, 2, 1, 2, 0, 5, 0, 2 )

735 .      matrix rowname  spMw1 =  spMw1

736 .      matrix rowname  spFw1 =  spFw1

737 .      matlist  spMw1

>      |      c1      c2      c3      c4      c5      c
> 6      c7      c8
-----
>      |
>      spMw1 |      1      2      1      1      1
> 2      2      1

738 .      matlist  spFw1

>      |      c1      c2      c3      c4      c5      c
> 6      c7      c8
-----
>      |
>      spFw1 |      1      2      1      2      0
> 5      0      2

739 .      matrix define H1pt2w1 = (  wkMw1 \  wkFw1 \  hmcrMw1 \  hmcrFw1 \  s
> pMw1 \  spFw1 )

740 .

```

```
741 .      matlist H1pt2w1
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 1	1	2					
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 2	0	2					
	spMw1	1	2	1	1	1	
> 2	2	1					
	spFw1	1	2	1	2	0	
> 5	0	2					

```
742 .      matrix colnames H1pt2w1 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
743 .      matrix rownames H1pt2w1 =  wkMw1 wkFw1 hmcrMw1 hmcrFw1 socprbMw1 socprb
> Fw1
```

```
744 .      matlist H1pt2w1
```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2	0	1					
	wkFw1	1	2	1	2	0	
> 1	1	2					
	hmcrMw1	1	2	1	1	0	
> 2	0	1					
	hmcrFw1	1	2	1	2	0	
> 2	0	2					
	socprbMw1	1	2	1	1	1	
> 2	2	1					
	socprbFw1	1	2	1	2	0	
> 5	0	2					

```

745 .
746 .
747 .
748 . *xx significant dose effect for females
749 .
750 . *xx no female moderators for Dose Social problem impact relationship
751 . scalar list
    MainEffhmcrFw1 = age
    MainEffhmcrMw1 = age
    hmcrMedFw1 = age bf4
    hmcrMedMw1 = radhlw1
    MainEffwkFw1 = age
    MainEffwkMw1 = age
    MainEffVactnMw1 = age radhlw1
    VactnMedFw1 = age illw1 radhlw1
    VactnMedMw1 = age
    VacatnModFw1 = none
    MainEffVactnFw1 = age radhlw1 bf7m
    SigDoseVactnFw1 = no
    VactnModMw1 = none
    inthobMedFw1 = age bf4 illw1 bf4m
    inthobMedMw1 = age
    inthobMw1 = age
    InthbModFw1 = none
    MainEffInthbFw1 = age radhlw1 bf4
    SigdoseInthbFw1 = no
    InthbModMw1 = none
    MainEffInthbMw1 = age radhlw1 shfamw1
    SigDoseInthbMw1 = no
    MainEffMw1 = radhlw1 bf4 bf40
    sxlifeMedMw1 = radhlw1
    sxlifeMedFw1 = age illw1 radhlw1 bf4 bf4m
    MainEffsxlifeFw1 = age bf4 bf4m
    SigDoseSxlifeFw1 = no
    SigDosesxlifeMw1 = no
    MainEffsxlifeMw1 = age bf4 bf40
    SigDosePrbfmhmMw1 = no
    vactnModMw1 = none
    SigDoseVactnMw1 = no
    SxLifeModFw1 = no
    sxlifeModFw1 = none
    sxlifeModMw1 = none
    MaineffhmcrMw1 = age bf4 bf40
    SigDoseMEhmcrW1 = no
    PrbfmhmMedFw1 = age bf4
    PrbfmhmMedMw1 = age
    MainEffPrbfmhmFw1 = age radhlw1 bf4
    MainEffPrbfmhmMw1 = age bf4
    PrbfmhmModFw1 = none

```

```

PrbfmhmModMw1 = none
SigDosePrbfmhmFw1 = no
SigDosePrbfhmMw1 = no
MainEffPrbfhmMw1 = age bf4
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
MainEffPrbsocMw1 = age bf4m
SigdoseMw1 = no
ProbsocMedFw1 = age bf4
ProbsocMedMw1 = radhlw1
ProbsocModFw1 = none
SigDoseProbsocMw1 = no
hmcrmedMw1 = radhlw1
hmcrmedFw1 = age b4 b40
SigdosehmcrFw1 = no
MainEffProbSocFw1 = age radhlw1 avgcumdosew1 shrelaw1 bf4
SigDoseProbsocFw1 = yes
PrbsocModMw1 = shjobw1Xd1 shrelaw1Xd1
    WkhmcrMw1 = age b4
    WkModFw1 = ageXd1
hmcareMedFw1 = age illw1
hmcareMedMw1 = age
SigDosehmcrFw1 = no
    wkMedMw1 = bf40
hmcrModFw1 = none
SigDoseHmcrFw1 = yes
    WkMedMw1 = bf40
hmcrModMw1 = none
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
VactnMedMw2 = 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

```

```

752 .
753 .
754 .
755 . *----- Chunk 5    Dose => Problems with the Family at home Impact
756 . title "4. H1 pt 2 wave 1  Dose = Fam Problems at home impact"

```

```

757 . forvalues j=1/1 {
      2. set more off
      3.
758 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
759 .   foreach var in HP2pbfhm {
      5.       forvalues k=1/2 {
      6. local wlbfbf1 bf4 bf9 bf10 bf11 bf14 bf15m bf20 bf22 bf30 bf40
      7.
760 . 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.

```

```

761 .      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 specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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 - BSIIsoma)
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 HP2pbfhm for wave= 1

chunk 5 H1 test:Gender= 1 model Wave = 1 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: occ5w1 != 0 predicts failure perfectly
occ5w1 dropped and 8 obs not used

note: occ6w1 != 0 predicts failure perfectly
occ6w1 dropped and 4 obs not used

note: occ7w1 != 0 predicts failure perfectly
occ7w1 dropped and 4 obs not used

note: marrw12 != 0 predicts failure perfectly
marrw12 dropped and 4 obs not used

note: marrw15 != 0 predicts success perfectly
marrw15 dropped and 1 obs not used

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

note: dvcew1 != 0 predicts failure perfectly
dvcew1 dropped and 1 obs not used

note: sepaw1 != 0 predicts failure perfectly
sepaw1 dropped and 1 obs not used

note: accdw1 != 0 predicts failure perfectly
accdw1 dropped and 6 obs not used

note: _Ieduc_6 omitted because of collinearity
note: marrw16 omitted because of collinearity

Logistic regression

Number of obs = 259
LR chi2(37) = 58.78
Prob > chi2 = 0.0128
Pseudo R2 = 0.4173

Log likelihood = -41.036775

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1140333	.0507477	2.25	0.025	.0145697	.2134969
_Ieduc_2	0	(omitted)				
_Ieduc_3	-.0489809	.8274219	-0.06	0.953	-1.670698	1.572736
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.3717243	1.234713	-0.30	0.763	-2.791717	2.048268
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w1	.0549567	3.40443	0.02	0.987	-6.617603	6.727516
occ2w1	-.6561172	3.427034	-0.19	0.848	-7.372981	6.060747
occ3w1	1.845881	3.621761	0.51	0.610	-5.25264	8.944401
occ4w1	-.738871	3.594017	-0.21	0.837	-7.783015	6.305273
occ5w1	0	(omitted)				
occ6w1	0	(omitted)				
occ7w1	0	(omitted)				
occ8w1	.7397449	3.652989	0.20	0.840	-6.419982	7.899471
marrw11	9.984281	2273.716	0.00	0.996	-4446.417	4466.386
marrw12	0	(omitted)				
marrw13	9.475183	2273.716	0.00	0.997	-4446.927	4465.877
marrw15	0	(omitted)				
marrw16	0	(omitted)				
inc1w1	-2.098091	3.351876	-0.63	0.531	-8.667648	4.471466
inc2w1	-1.263123	3.216941	-0.39	0.695	-7.568212	5.041965
inc3w1	-1.666932	3.248691	-0.51	0.608	-8.034249	4.700384
inc4w1	-2.798082	3.810066	-0.73	0.463	-10.26567	4.669509
radhlw1	.0221794	.012356	1.80	0.073	-.0020379	.0463968
havmil	-.0042208	.0093253	-0.45	0.651	-.0224981	.0140566
avgcumdosew1	-1.041178	.9206409	-1.13	0.258	-2.845601	.7632452
bf1	-.0255316	.0778527	-0.33	0.743	-.1781201	.127057
bf4	-.2441414	.1077011	-2.27	0.023	-.4552317	-.0330512
bf9	-.0547201	.051475	-1.06	0.288	-.1556092	.046169
bf10	-.2223925	.2030607	-1.10	0.273	-.6203843	.1755992
bf11	-.0227027	.1366459	-0.17	0.868	-.2905237	.2451183
bf14	.0001079	.0001172	0.92	0.357	-.0001219	.0003377
bf15m	0	(omitted)				
bf20	.0093433	.0710822	0.13	0.895	-.1299752	.1486619
bf22	.000374	.0002074	1.80	0.071	-.0000324	.0007805
bf30	-.0000361	.0007108	-0.05	0.959	-.0014293	.001357

bf40	-.5322776	.3877192	-1.37	0.170	-1.292193	.227638
deawl	.139745	.7195497	0.19	0.846	-1.270547	1.550036
dvcewl	0	(omitted)				
sepawl	0	(omitted)				
accdwl	0	(omitted)				
movewl	-.9959846	2.338912	-0.43	0.670	-5.580168	3.588199
illwl	.0424127	.9714262	0.04	0.965	-1.861548	1.946373
shfamwl	.0013379	.0148676	0.09	0.928	-.0278022	.0304779
shhlwl	-.002734	.0255506	-0.11	0.915	-.0528123	.0473444
shjobwl	-.0385947	.0207074	-1.86	0.062	-.0791804	.0019911
shrelawl	.004462	.0134181	0.33	0.739	-.0218371	.0307611
suprtwl	.0496362	.0609811	0.81	0.416	-.0698846	.169157
suchrwl	-.0362505	.1014181	-0.36	0.721	-.2350263	.1625254
havmilsq	4.65e-06	9.99e-06	0.46	0.642	-.0000149	.0000242
_cons	-11.63773	2273.725	-0.01	0.996	-4468.057	4444.781

Note: 8 failures and 0 successes completely determined.

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	9	2	11
-	11	237	248
Total	20	239	259

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	45.00%
Specificity	$\Pr(- \sim D)$	99.16%
Positive predictive value	$\Pr(D +)$	81.82%
Negative predictive value	$\Pr(\sim D -)$	95.56%

False + rate for true ~D	$\Pr(+ \sim D)$	0.84%
False - rate for true D	$\Pr(- D)$	55.00%
False + rate for classified +	$\Pr(\sim D +)$	18.18%
False - rate for classified -	$\Pr(D -)$	4.44%

Correctly classified	94.98%
----------------------	--------

Logistic model for HP2pbfhm, goodness-of-fit test

```

        number of observations =      259
number of covariate patterns =      259
        Pearson chi2(221) =      143.82
            Prob > chi2 =      1.0000

```

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

```

Log-Lik Intercept Only:      -70.429      Log-Lik Full Model:      -41.037
D(206):                      82.074      LR(37):                  58.785
                               Prob > LR:                  0.013
McFadden's R2:              0.417      McFadden's Adj R2:      -0.335
Maximum Likelihood R2:      0.203      Cragg & Uhler's R2:    0.484
McKelvey and Zavoina's R2:  0.857      Efron's R2:            0.352
Variance of y*:             23.001      Variance of error:      3.290
Count R2:                   0.950      Adj Count R2:          0.350
AIC:                        0.726      AIC*n:                 188.074
BIC:                       -1062.633     BIC':                  146.818
Full main model for HP2pbfhm for wave= 1

```

chunk 5 H1 test:Gender= 2 model Wave = 1 for HP2pbfhm

```

i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: marrw12 != 0 predicts failure perfectly
      marrw12 dropped and 4 obs not used

```

```

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

```

note: _Ieduc_8 omitted because of collinearity

```

Logistic regression                                Number of obs   =      343
                                                    LR chi2(49)    =      131.00
                                                    Prob > chi2     =      0.0000
Log likelihood = -71.53941                        Pseudo R2      =      0.4780

```

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1418493	.0387097	3.66	0.000	.0659796	.217719
_Ieduc_2	17.22542	4534.447	0.00	0.997	-8870.128	8904.579
_Ieduc_3	17.37005	4534.447	0.00	0.997	-8869.983	8904.723
_Ieduc_4	17.2893	4534.447	0.00	0.997	-8870.064	8904.643
_Ieduc_5	17.58061	4534.447	0.00	0.997	-8869.773	8904.934
_Ieduc_6	17.54436	4534.447	0.00	0.997	-8869.809	8904.898
_Ieduc_7	19.56629	4534.448	0.00	0.997	-8867.789	8906.922
_Ieduc_8	0	(omitted)				
occ1w1	-2.933908	3.752469	-0.78	0.434	-10.28861	4.420796
occ2w1	-3.629362	3.805266	-0.95	0.340	-11.08755	3.828822
occ3w1	-2.149571	3.775043	-0.57	0.569	-9.54852	5.249378

occ4w1	-3.08403	3.884516	-0.79	0.427	-10.69754	4.529481
occ5w1	-1.54127	3.940317	-0.39	0.696	-9.264149	6.181609
occ6w1	-4.518852	4.376561	-1.03	0.302	-13.09675	4.05905
occ7w1	-.5209646	3.827304	-0.14	0.892	-8.022342	6.980413
occ8w1	-.6982657	3.788908	-0.18	0.854	-8.124388	6.727857
marrw11	6.563183	2.259003	2.91	0.004	2.135619	10.99075
marrw12	0	(omitted)				
marrw13	3.664968	1.807756	2.03	0.043	.1218322	7.208105
marrw15	4.919489	2.358945	2.09	0.037	.2960419	9.542936
marrw16	3.80604	2.237487	1.70	0.089	-.5793546	8.191435
inclw1	.8452115	3.777625	0.22	0.823	-6.558798	8.249221
inc2w1	2.888908	3.720317	0.78	0.437	-4.402779	10.18059
inc3w1	2.900029	3.700306	0.78	0.433	-4.352438	10.1525
inc4w1	3.648558	4.001972	0.91	0.362	-4.195162	11.49228
radhlw1	.0284271	.0105574	2.69	0.007	.0077349	.0491194
havmil	-.0074706	.0174749	-0.43	0.669	-.0417209	.0267796
avgcumdosew1	-.072348	.4728314	-0.15	0.878	-.9990805	.8543844
bf1	.0059636	.0469599	0.13	0.899	-.086076	.0980033
bf4	-.4047147	.0856612	-4.72	0.000	-.5726076	-.2368217
bf9	-.0595004	.0425833	-1.40	0.162	-.1429621	.0239614
bf10	-.0062201	.0202319	-0.31	0.759	-.045874	.0334338
bf11	-.0101918	.0656234	-0.16	0.877	-.1388112	.1184277
bf14	-.0003249	.0001287	-2.52	0.012	-.0005772	-.0000727
bf15m	0	(omitted)				
bf20	-.0168987	.0398949	-0.42	0.672	-.0950913	.0612938
bf22	.0003491	.0001303	2.68	0.007	.0000938	.0006044
bf30	.0000363	.0004332	0.08	0.933	-.0008127	.0008853
bf40	-.6041257	.200322	-3.02	0.003	-.9967496	-.2115017
deaw1	-.2106609	.3829692	-0.55	0.582	-.9612668	.539945
dvcew1	3.227642	1.990455	1.62	0.105	-.6735776	7.128863
sepaw1	-1.961135	2.530088	-0.78	0.438	-6.920017	2.997746
accdw1	-1.15855	1.327999	-0.87	0.383	-3.76138	1.44428
movew1	.8502008	.7012493	1.21	0.225	-.5242225	2.224624
illw1	1.167312	.5375125	2.17	0.030	.1138066	2.220817
shfamw1	-.0177543	.0110296	-1.61	0.107	-.039372	.0038633
shhlw1	-.0133242	.0167146	-0.80	0.425	-.0460843	.0194358
shjobw1	.0113593	.0116917	0.97	0.331	-.0115561	.0342746
shrelaw1	.0021827	.0102849	0.21	0.832	-.0179754	.0223408
suprtw1	.0039965	.0137794	0.29	0.772	-.0230105	.0310036
suchrw1	-.0313303	.0297859	-1.05	0.293	-.0897095	.027049
havmilsq	-5.84e-06	.0000521	-0.11	0.911	-.0001079	.0000962
_cons	-26.74862	4534.45	-0.01	0.995	-8914.107	8860.609

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	26	5	31
-	21	291	312
Total	47	296	343

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	55.32%
Specificity	$\Pr(- \sim D)$	98.31%
Positive predictive value	$\Pr(D +)$	83.87%
Negative predictive value	$\Pr(\sim D -)$	93.27%
False + rate for true ~D	$\Pr(+ \sim D)$	1.69%
False - rate for true D	$\Pr(- D)$	44.68%
False + rate for classified +	$\Pr(\sim D +)$	16.13%
False - rate for classified -	$\Pr(D -)$	6.73%
Correctly classified		92.42%

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      343
number of covariate patterns =    343
Pearson chi2(293) =      979.77
Prob > chi2 =      0.0000

```

Measures of Fit for logistic of HP2pbfhm

Log-Lik Intercept Only:	-137.038	Log-Lik Full Model:	-71.539
D(290):	143.079	LR(49):	130.998
		Prob > LR:	0.000
McFadden's R2:	0.478	McFadden's Adj R2:	0.091
Maximum Likelihood R2:	0.317	Cragg & Uhler's R2:	0.577
McKelvey and Zavoina's R2:	0.915	Efron's R2:	0.495
Variance of y*:	38.594	Variance of error:	3.290
Count R2:	0.924	Adj Count R2:	0.447
AIC:	0.726	AIC*n:	249.079
BIC:	-1549.863	BIC':	155.051

```

762 .
763 .
764 . title4 "Partly Trimmed male wave 1  Dose => Problems with Family at home mod
> els"

```

Partly Trimmed male wave 1 Dose => Problems with Family at home models

```

765 . local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40

766 . logit HP2pbfhm age bf4 bf22  radhlw1 avgcumdosew1  shjobw1 suprtw1 ///
>      illw1 if gender==1, iterate(50)

```

```

Iteration 0:  log likelihood = -81.506236
Iteration 1:  log likelihood = -70.36767
Iteration 2:  log likelihood = -63.735881
Iteration 3:  log likelihood = -63.262978
Iteration 4:  log likelihood = -63.251084
Iteration 5:  log likelihood = -63.251044
Iteration 6:  log likelihood = -63.251044

```

Logistic regression	Number of obs	=	340
	LR chi2(8)	=	36.51
	Prob > chi2	=	0.0000
Log likelihood = -63.251044	Pseudo R2	=	0.2240

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0417694	.0232436	1.80	0.072	-.0037872	.0873261
bf4	-.1944454	.0674328	-2.88	0.004	-.3266114	-.0622795
bf22	.0001979	.0001096	1.81	0.071	-.0000169	.0004126
radhlw1	.0156873	.0077256	2.03	0.042	.0005455	.0308292
avgcumdosew1	-.7288118	.6058279	-1.20	0.229	-1.916213	.4585891
shjobw1	-.0246328	.0097441	-2.53	0.011	-.0437309	-.0055347
suprtw1	-.0367192	.0154384	-2.38	0.017	-.0669779	-.0064605
illw1	1.081626	.5960837	1.81	0.070	-.0866765	2.249929
_cons	-2.68461	1.769319	-1.52	0.129	-6.152411	.7831919

Note: 1 failure and 0 successes completely determined.

```
767 .
768 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	1	1	2
-	21	317	338
Total	22	318	340

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

Sensitivity	$\Pr(+ D)$	4.55%
Specificity	$\Pr(- \sim D)$	99.69%
Positive predictive value	$\Pr(D +)$	50.00%
Negative predictive value	$\Pr(\sim D -)$	93.79%
False + rate for true ~D	$\Pr(+ \sim D)$	0.31%
False - rate for true D	$\Pr(- D)$	95.45%
False + rate for classified +	$\Pr(\sim D +)$	50.00%
False - rate for classified -	$\Pr(D -)$	6.21%
Correctly classified		93.53%

```
769 . estat gof
```

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    337
    Pearson chi2(328) =    247.99
        Prob > chi2 =      0.9997
```

```
770 . fitstat
```

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-81.506	Log-Lik Full Model:	-63.251
D(331):	126.502	LR(8):	36.510
		Prob > LR:	0.000
McFadden's R2:	0.224	McFadden's Adj R2:	0.114
Maximum Likelihood R2:	0.102	Cragg & Uhler's R2:	0.267
McKelvey and Zavoina's R2:	0.537	Efron's R2:	0.137
Variance of y*:	7.110	Variance of error:	3.290
Count R2:	0.935	Adj Count R2:	0.000
AIC:	0.425	AIC*n:	144.502
BIC:	-1802.879	BIC':	10.121

```
771 .
```

```
772 . title4 "trimmed male main effects wv 1" " Dose => Problems with Family at ho
> me models"
```

```
trimmed male main effects wv 1
```

```
773 . local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40
```

```
774 . sw, pr(.1):logit HP2pbfhm age sepaw1 dvcew1 radhlw1 avgcumdosew1 bf4 suprtw
> 1 ///
```

```
> havmilsq illw1 if gender==1, iterate(50)
note: sepaw1 dropped because of estimability
note: dvcew1 dropped because of estimability
note: o.sepaw1 dropped because of estimability
note: o.dvcew1 dropped because of estimability
note: 6 obs. dropped because of estimability
begin with full model
p = 0.7261 >= 0.1000 removing havmilsq
p = 0.3270 >= 0.1000 removing avgcumdosew1
p = 0.1493 >= 0.1000 removing radhlw1
p = 0.1420 >= 0.1000 removing suprtw1
p = 0.5106 >= 0.1000 removing illw1
```

```
Logistic regression
```

```
Log likelihood = -65.847499
```

Number of obs	=	334
LR chi2(2)	=	19.70
Prob > chi2	=	0.0001
Pseudo R2	=	0.1301

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.043747	.0220586	1.98	0.047	.0005129	.0869811
bf4	-.1234479	.0425264	-2.90	0.004	-.2067982	-.0400977
_cons	-3.800943	1.442	-2.64	0.008	-6.627212	-.9746754

```

775 .
776 . estat class

```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	20	314	334
Total	20	314	334

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	$\Pr(\sim D -)$	94.01%
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 -	$\Pr(D -)$	5.99%
Correctly classified		94.01%

777 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	334
number of covariate patterns =	219
Pearson chi2(216) =	205.20
Prob > chi2 =	0.6901

778 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-75.697	Log-Lik Full Model:	-65.847
D(331):	131.695	LR(2):	19.699
		Prob > LR:	0.000
McFadden's R2:	0.130	McFadden's Adj R2:	0.090
Maximum Likelihood R2:	0.057	Cragg & Uhler's R2:	0.157
McKelvey and Zavoina's R2:	0.221	Efron's R2:	0.091
Variance of y*:	4.225	Variance of error:	3.290
Count R2:	0.940	Adj Count R2:	0.000
AIC:	0.412	AIC*n:	137.695
BIC:	-1791.793	BIC':	-8.077

779 .

780 . scalar MainEffPrbfhmMw1 = "age bf4"

781 . scalar SigDosePrbfhmMw1 = "no"

782 . // construction of moderators for male model

783 .

```
784 . foreach var in age bf4 {  
      2.  cap gen `var'Xd1 = `var'*avgcumdosew1  
      3.  }
```

785 .

```

786 .
787 .
788 .
789 . *****
> **
790 . *-----chunk 6 continued -testing moderators and none found for males
791 . local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40

792 .
793 .
794 . title4 "fully Trimmed male main effects wv 1" ///
> "Dose => Problems with Family at home models"

```

fully Trimmed male main effects wv 1

```

795 . local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40

796 . logit HP2pbfhm age radhlw1 avgcumdosew1 ///
> bf4Xd1 ageXd1 if ///
> gender==1, iterate(50)

```

```

Iteration 0: log likelihood = -81.506236
Iteration 1: log likelihood = -73.611243
Iteration 2: log likelihood = -71.601053
Iteration 3: log likelihood = -71.266265
Iteration 4: log likelihood = -71.252753
Iteration 5: log likelihood = -71.252739
Iteration 6: log likelihood = -71.252739

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	20.51
	Prob > chi2	=	0.0010
Log likelihood = -71.252739	Pseudo R2	=	0.1258

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0372929	.0360915	1.03	0.301	-.0334452	.108031
radhlw1	.0167822	.0070862	2.37	0.018	.0028936	.0306709
avgcumdosew1	-1.15754	8.877823	-0.13	0.896	-18.55775	16.24267
bf4Xd1	-.1079495	.1337235	-0.81	0.420	-.3700428	.1541438
ageXd1	.024333	.13587	0.18	0.858	-.2419673	.2906334
_cons	-5.341428	2.129704	-2.51	0.012	-9.515572	-1.167284

Note: 1 failure and 0 successes completely determined.

```
797 .
798 . 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%

```
799 . estat gof
```

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    328
    Pearson chi2(322) =    344.70
        Prob > chi2 =    0.1839
```

800 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-81.506	Log-Lik Full Model:	-71.253
D(334):	142.505	LR(5):	20.507
		Prob > LR:	0.001
McFadden's R2:	0.126	McFadden's Adj R2:	0.052
Maximum Likelihood R2:	0.059	Cragg & Uhler's R2:	0.154
McKelvey and Zavoina's R2:	0.526	Efron's R2:	0.077
Variance of y*:	6.942	Variance of error:	3.290
Count R2:	0.935	Adj Count R2:	0.000
AIC:	0.454	AIC*n:	154.505
BIC:	-1804.362	BIC':	8.638

801 .

802 . scalar SigDosePrbfmhmMw1 = "no"

803 . scalar PrbfmhmModMw1 = "none"

804 . scalar MainEffPrbfmhmMw1= "age bf4"

805 . * 3 main effects signif no main effect for dose for males

806 .

807 .

808 . *-----Chunk 6 continued -testing meditors for females

809 . title4 "Partly Trimmed female wave 1" "Dose => Problems with Family at home
> models"

Partly Trimmed female wave 1

810 . local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40

811 . logit HP2pbfhm age radhlw1 avgcumdosew1 bf4 if gender==2, iterate(50)

Iteration 0: log likelihood = **-139.75789**
Iteration 1: log likelihood = **-110.07066**
Iteration 2: log likelihood = **-103.23731**
Iteration 3: log likelihood = **-103.06224**
Iteration 4: log likelihood = **-103.0617**
Iteration 5: log likelihood = **-103.0617**

Logistic regression

Log likelihood = **-103.0617**

Number of obs	=	362
LR chi2(4)	=	73.39
Prob > chi2	=	0.0000
Pseudo R2	=	0.2626

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0490304	.0173334	2.83	0.005	.0150575	.0830032
radhlw1	.0175548	.0055923	3.14	0.002	.0065942	.0285154
avgcumdosew1	-.0824579	.2858577	-0.29	0.773	-.6427286	.4778129
bf4	-.1768305	.0371748	-4.76	0.000	-.2496918	-.1039692
_cons	-4.266136	1.122392	-3.80	0.000	-6.465984	-2.066287

```
812 .
813 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	14	5	19
-	33	310	343
Total	47	315	362

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

Sensitivity	$\Pr(+ D)$	29.79%
Specificity	$\Pr(- \sim D)$	98.41%
Positive predictive value	$\Pr(D +)$	73.68%
Negative predictive value	$\Pr(\sim D -)$	90.38%

False + rate for true ~D	$\Pr(+ \sim D)$	1.59%
False - rate for true D	$\Pr(- D)$	70.21%
False + rate for classified +	$\Pr(\sim D +)$	26.32%
False - rate for classified -	$\Pr(D -)$	9.62%

Correctly classified	89.50%
----------------------	--------

814 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	362
number of covariate patterns =	360
Pearson chi2(355) =	358.55
Prob > chi2 =	0.4373

815 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-139.758	Log-Lik Full Model:	-103.062
D(357):	206.123	LR(4):	73.392
		Prob > LR:	0.000
McFadden's R2:	0.263	McFadden's Adj R2:	0.227
Maximum Likelihood R2:	0.184	Cragg & Uhler's R2:	0.341
McKelvey and Zavoina's R2:	0.420	Efron's R2:	0.242
Variance of y*:	5.668	Variance of error:	3.290
Count R2:	0.895	Adj Count R2:	0.191
AIC:	0.597	AIC*n:	216.123
BIC:	-1897.194	BIC':	-49.826

816 .

817 . scalar SigDosePrbfbmhmFw1="no"

818 .

819 . *-----Chunk 6 continued -testing meditors for females

820 . title4 "More partly female Trimmed wave 1" "Dose => Problems with Family at
> home models"

More partly female Trimmed wave 1

821 . local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40

```
822 . 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

```
823 .
```

```
824 . 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(- ~D)	99.05%
Positive predictive value	Pr(D +)	80.00%
Negative predictive value	Pr(~D -)	89.94%
False + rate for true ~D	Pr(+ ~D)	0.95%
False - rate for true D	Pr(- D)	74.47%
False + rate for classified +	Pr(~D +)	20.00%
False - rate for classified -	Pr(D -)	10.06%

Correctly classified **89.53%**

825 . 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

826 . 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

827 .

828 . scalar SigDosePrbfmhmFw1="no"

829 . scalar MainEffPrbfmhmFw1 = "age radhlw1 bf4"

830 . * 3 significant main effects for females

831 . * no significant main effect for dose

832 .

833 . * constructing moderators

```

834 .
835 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd1 = `var'*avgcumdosew1
      3. }

836 .
837 .
838 . title4 "testing female moderator effects:  no moderator effects for females"

```

```
testing female moderator effects:  no moderator effects for females
```

```

839 .
840 . logit HP2pbfhm age bf4 bf40 ageXd1 bf4Xd1 bf40Xd1 if gender==2, iterate(50)

```

```

Iteration 0:  log likelihood = -139.89675
Iteration 1:  log likelihood = -112.27547
Iteration 2:  log likelihood = -106.13405
Iteration 3:  log likelihood = -105.51351
Iteration 4:  log likelihood = -105.50804
Iteration 5:  log likelihood = -105.50803
Iteration 6:  log likelihood = -105.50803

```

Logistic regression	Number of obs	=	363
	LR chi2(6)	=	68.78
	Prob > chi2	=	0.0000
Log likelihood = -105.50803	Pseudo R2	=	0.2458

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0608384	.0177875	3.42	0.001	.0259756	.0957012
bf4	-.2060931	.0500059	-4.12	0.000	-.304103	-.1080832
bf40	-.1074502	.1266208	-0.85	0.396	-.3556225	.140722
ageXd1	.0103515	.0150265	0.69	0.491	-.0190999	.039803
bf4Xd1	.0257937	.0948566	0.27	0.786	-.1601219	.2117093
bf40Xd1	-.2219543	.2551348	-0.87	0.384	-.7220092	.2781007
_cons	-3.197134	1.118642	-2.86	0.004	-5.389632	-1.004635

841 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

```

      number of observations =      363
number of covariate patterns =      359
      Pearson chi2(352) =      359.71
          Prob > chi2 =      0.3769

```

842 . estat class

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	13	4	17
-	34	312	346
Total	47	316	363

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

Sensitivity	$\Pr(+ D)$	27.66%
Specificity	$\Pr(- \sim D)$	98.73%
Positive predictive value	$\Pr(D +)$	76.47%
Negative predictive value	$\Pr(\sim D -)$	90.17%
False + rate for true ~D	$\Pr(+ \sim D)$	1.27%
False - rate for true D	$\Pr(- D)$	72.34%
False + rate for classified +	$\Pr(\sim D +)$	23.53%
False - rate for classified -	$\Pr(D -)$	9.83%
Correctly classified		89.53%

843 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-139.897	Log-Lik Full Model:	-105.508
D(356):	211.016	LR(6):	68.777
		Prob > LR:	0.000
McFadden's R2:	0.246	McFadden's Adj R2:	0.196
Maximum Likelihood R2:	0.173	Cragg & Uhler's R2:	0.321
McKelvey and Zavoina's R2:	0.404	Efron's R2:	0.226
Variance of y*:	5.517	Variance of error:	3.290
Count R2:	0.895	Adj Count R2:	0.191
AIC:	0.620	AIC*n:	225.016
BIC:	-1887.391	BIC':	-33.411

844 .

845 . scalar PrbfmhmModFw1="none"

846 .

847 . *****
> ****

848 . *-----Chunk 6 continued testing mediating effects for Problems with fami
> ly

849 . * at home

850 .

851 .

852 . 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)

853 . glm age avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1331.608**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	148.5632
Deviance	= 50214.37624	(1/df) Deviance	=	148.5632
Pearson	= 50214.37624	(1/df) Pearson	=	148.5632
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]

Log likelihood	= -1331.607976	<u>AIC</u>	= 7.844753
		<u>BIC</u>	= 48244.19

	OIM					
age	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
854 . glm HP2pbfhm age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 163.1004
Iteration 2:    deviance = 152.8997
Iteration 3:    deviance = 151.9532
Iteration 4:    deviance = 151.9347
Iteration 5:    deviance = 151.9347
Iteration 6:    deviance = 151.9347
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 151.9346518	(1/df) Deviance	=	.4495108
Pearson = 324.8005072	(1/df) Pearson	=	.9609482

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

```

855 .
856 . glm bf4  avgcumdosew1 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1026.9659**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	24.75428
Deviance = 8366.946191	(1/df) Deviance	=	24.75428
Pearson = 8366.946191	(1/df) Pearson	=	24.75428
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	6.05274
Log likelihood = -1026.965868	<u>BIC</u>	=	6396.763

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.1031788	.161925	-0.64	0.524	-.4205461	.2141884
_cons	12.54134	.2786337	45.01	0.000	11.99523	13.08746

```

857 . 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.)

```

858 .
859 . * age is a mediating effect for females for Dose=> Problems with family at h
    > ome
860 . glm age avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.325**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.455
Deviance = 49260.25928	(1/df) Deviance	=	136.455
Pearson = 49260.25928	(1/df) Pearson	=	136.455

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

	<u>AIC</u>	=	7.759366
Log likelihood = -1406.325011	<u>BIC</u>	=	47132.38

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```

861 . 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.)

```

862 .
863 . * bf4 is a mediating effect for females for Dose=> Problems with family at ho
    > me
864 . glm bf4 avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1109.0162**

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                      Residual df      =       361
                                          Scale parameter =   26.52082
Deviance          =   9574.015672          (1/df) Deviance =   26.52082
Pearson           =   9574.015672          (1/df) Pearson  =   26.52082

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

                                          AIC              =   6.121302
Log likelihood    =  -1109.016226          BIC              =   7446.136

```

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```
865 . glm HP2pbfhm bf4 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 240.0481
Iteration 2: deviance = 229.4916
Iteration 3: deviance = 228.6166
Iteration 4: deviance = 228.5986
Iteration 5: deviance = 228.5985
Iteration 6: deviance = 228.5985
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML Fisher scoring                 Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 228.5985175                        (1/df) Deviance =  .6332369
Pearson           = 299.6186696                        (1/df) Pearson  =  .8299686
```

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

```
BIC = -1899.281
```

HP2pbfhm	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.1229375	.0145262	-8.46	0.000	-.1514083	-.0944667
_cons	-.0739521	.1322299	-0.56	0.576	-.3331179	.1852138

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

```
866 .
```

```
867 .
```

```
868 . glm bf6 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1783.6957
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML                                 Residual df     =       361
Scale parameter = 1091.352
Deviance          = 393977.8948                        (1/df) Deviance = 1091.352
Pearson           = 393977.8948                        (1/df) Pearson  = 1091.352
```

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

```
Log likelihood    = -1783.695663                        AIC              =  9.838544
                                                           BIC              =  391850
```

bf6	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	4.907676	3.160857	1.55	0.121	-1.287489	11.10284
_cons	53.46082	2.032533	26.30	0.000	49.47713	57.44452

```
869 . 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.)

```
870 .
```

```

871 .
872 . glm bf7  avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-902.44388**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	8.497656
Deviance = 3067.65399	(1/df) Deviance	=	8.497656
Pearson = 3067.65399	(1/df) Pearson	=	8.497656
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	4.983162
Log likelihood = -902.4438834	<u>BIC</u>	=	939.7746

bf7	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.3565771	.2789151	-1.28	0.201	-.9032407	.1900865
_cons	1.056277	.1793514	5.89	0.000	.7047548	1.407799

```

873 . 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.)

```

874 .
875 . scalar MainEffPrbfhmMw1 = "age bf4"

876 . scalar SigDosePrbfhmMw1 = "no"

877 . scalar SigDosePrbfmhmFw1="no"          // fix in others

878 . scalar PrbfmhmModMw1 = "none"

879 . scalar PrbfmhmModFw1="none"

880 . scalar MainEffPrbfmhmMw1= "age bf4"

881 .
882 . scalar MainEffPrbfmhmFw1 = "age radhlw1 bf4"

883 .
884 . scalar PrbfmhmMedMw1 = "age"

885 . scalar PrbfmhmMedFw1 = "age bf4"

886 . * Summary of dose=problems with family at home mediating effects
887 . * males mediators age 1
888 . * females mediators age and BSIsoma rescaled (bf4) 2
889 .
890 . title4 "4. Summary matrix for problems with family at home"

```

4. Summary matrix for problems with family at home

```

891 .      matrix define prbfamMw1 = J(1,8, 0)

892 .          matrix define prbfamFw1 = J(1,8, 0)

893 . matrix colnames prbfamMw1=  hypnum ptnum wave gender medsig numMASig numMods
    > ig numMed

894 .          matrix colnames prbfamFw1=  hypnum ptnum wave gender medsig numMASig
    > numModsig numMed

895 .      matrix define prbfamMw1= (1, 2, 1, 1, 0, 2, 0, 0 )

896 .          matrix define prbfamFw1= (1, 2, 1, 2, 0, 3, 0, 2)

897 .          matrix rowname prbfamMw1 = prbfamMw1

898 .          matrix rowname prbfamFw1 = prbfamFw1

899 .          matlist prbfamMw1

> 6      |      c1      c2      c3      c4      c5      c
      c7      c8
-----|-----
> prbfamMw1 |      1      2      1      1      0
> 2      0      0

900 .          matlist prbfamFw1

> 6      |      c1      c2      c3      c4      c5      c
      c7      c8
-----|-----
> prbfamFw1 |      1      2      1      2      0
> 3      0      2

901 .          matrix define H1pt2w1 = ( wkMw1 \ wkFw1 \ hmcrMw1 \ hmcrFw1 \ spMw1
    > \ spFw1 \ prbfamMw1 \ prbfamFw1)

```

```

902 .
903 .      matlist H1pt2w1

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 1	1	2					
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 2	0	2					
	spMw1	1	2	1	1	1	
> 2	2	1					
	spFw1	1	2	1	2	0	
> 5	0	2					
	prbfamMw1	1	2	1	1	0	
> 2	0	0					
	prbfamFw1	1	2	1	2	0	
> 3	0	2					

```

904 .      matrix colnames H1pt2w1 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed

```

```

905 .      matrix rownames H1pt2w1 =   wkMw1 wkFw1 hmcrMw1 hmcrFw1 prbsocMw1 prbsoc
> Fw1 prbfhmMw1 prbfhmFw1

```

```

906 .      matlist H1pt2w1

```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2	0	1					
	wkFw1	1	2	1	2	0	
> 1	1	2					
	hmcrMw1	1	2	1	1	0	
> 2	0	1					
	hmcrFw1	1	2	1	2	0	
> 2	0	2					
	prbsocMw1	1	2	1	1	1	
> 2	2	1					
	prbsocFw1	1	2	1	2	0	
> 5	0	2					
	prbfhmMw1	1	2	1	1	0	

```

> 2      0      0
prbfhmFw1 |      1      2      1      2      0
> 3      0      2

```

```

907 .
908 .
909 .
910 . *****
> *****
911 . *-----Chunk 7   Dose==> problems with sex life impact
912 . * Chunk 7   General model for all part 2 of Nottingham Health Profile
913 .
914 . title "5.   H1 pt 2 wave 1 part2 H1 dose sex life impact"

```

```

*****
> *
*****
> *
*****                                     *****
> *
*****                                     *****
> *
*****          5.   H1 pt 2 wave 1 part2 H1 dose sex life impact          *****
> *
*****                                     *****
> *
*****                                     *****
> *
*****                                     18 Jun 2012   18:16:34   *****
> *
*****
> *
*****
> *

```

```

915 .
916 . forvalues j=1/1 {
      2. set more off
      3.
917 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
918 .   foreach var in HP2sxlife {
      5.       forvalues k=1/2 {
      6.         local w1bf bf1 bf4 bf9 bf10 bf11 bf14 bf15m bf20 bf22 bf30 bf40
      7.         title "Full Nottingham Part 2 subscale models for male & females" ///
      > "Full main model for `var' for wave= `j' " ///
      > "chunk 7 H1 test:Gender= `k' model Wave = `j' for `e(depvar)' "
      8.         di _skip(4)
      9.
919 .         di _skip(4)
      10.
920 .
921 .         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 radhlw1 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

marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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= 1
> *
*****
chunk 7 H1 test:Gender= 1 model Wave = 1 for HP2pbfhm
> *
*****
> *
*****
> *
*****
18 Jun 2012 18:16:34
> *
*****
*****
> *
*****

```

> *

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: marrw12 != 0 predicts failure perfectly

 marrw12 dropped and 5 obs not used

note: marrw15 != 0 predicts success perfectly

 marrw15 dropped and 1 obs not used

note: bf15m != 0 predicts failure perfectly

 bf15m dropped and 20 obs not used

note: dvcew1 != 0 predicts failure perfectly

 dvcew1 dropped and 2 obs not used

note: sepaw1 != 0 predicts success perfectly

 sepaw1 dropped and 1 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw16 omitted because of collinearity

note: radhlw1 omitted because of collinearity

Logistic regression

Number of obs = 288

LR chi2(43) = 149.61

Prob > chi2 = 0.0000

Pseudo R2 = 0.4904

Log likelihood = -77.748591

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.136472	.0366667	3.72	0.000	.0646066	.2083374
_Ieduc_2	.9061528	2.373186	0.38	0.703	-3.745206	5.557512
_Ieduc_3	1.126364	2.057334	0.55	0.584	-2.905936	5.158664
_Ieduc_4	0	(omitted)				
_Ieduc_5	.4719974	2.096628	0.23	0.822	-3.637317	4.581312
_Ieduc_6	1.043192	2.050556	0.51	0.611	-2.975823	5.062208
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w1	-2.803127	2.35705	-1.19	0.234	-7.422861	1.816606
occ2w1	-2.898533	2.359872	-1.23	0.219	-7.523797	1.726731

occ3w1	-3.662112	2.523184	-1.45	0.147	-8.607462	1.283238
occ4w1	-2.435194	2.370439	-1.03	0.304	-7.08117	2.210782
occ5w1	-5.879936	2.735652	-2.15	0.032	-11.24172	-.5181554
occ6w1	-.066721	2.7504	-0.02	0.981	-5.457405	5.323963
occ7w1	-3.83747	3.050515	-1.26	0.208	-9.81637	2.14143
occ8w1	-2.95823	2.351973	-1.26	0.208	-7.568013	1.651553
marrw11	8.464083	907.837	0.01	0.993	-1770.864	1787.792
marrw12	0	(omitted)				
marrw13	6.092151	907.8374	0.01	0.995	-1773.236	1785.421
marrw15	0	(omitted)				
marrw16	0	(omitted)				
inc1w1	5.396209	3.075845	1.75	0.079	-.6323357	11.42475
inc2w1	5.263232	2.974878	1.77	0.077	-.567422	11.09389
inc3w1	4.958244	2.931498	1.69	0.091	-.7873865	10.70387
inc4w1	3.505305	3.128247	1.12	0.262	-2.625946	9.636556
radhlw1	.005437	.0073698	0.74	0.461	-.0090075	.0198816
havmil	-.0008616	.007551	-0.11	0.909	-.0156613	.0139381
avgcumdosew1	.0450522	.105977	0.43	0.671	-.162659	.2527634
bf1	.0721133	.0467218	1.54	0.123	-.0194598	.1636864
bf4	-.3272064	.0723192	-4.52	0.000	-.4689494	-.1854635
bf9	-.0022701	.0341874	-0.07	0.947	-.0692761	.0647359
bf10	-.0510813	.0368445	-1.39	0.166	-.1232952	.0211325
bf11	.2631067	.1226965	2.14	0.032	.0226261	.5035874
bf14	-.0000418	.0000857	-0.49	0.626	-.0002098	.0001262
bf15m	0	(omitted)				
bf20	-.0698283	.0411461	-1.70	0.090	-.1504731	.0108166
bf22	.0001486	.0001281	1.16	0.246	-.0001025	.0003997
bf30	-.0002299	.0004245	-0.54	0.588	-.0010618	.0006021
bf40	.0950229	.1871851	0.51	0.612	-.2718532	.4618989
deaw1	.659494	.4055746	1.63	0.104	-.1354176	1.454406
dvcew1	0	(omitted)				
sepaw1	0	(omitted)				
accdw1	-.8665368	1.711081	-0.51	0.613	-4.220195	2.487121
movew1	1.595582	.6025445	2.65	0.008	.4146162	2.776547
illw1	-.39832	.6674749	-0.60	0.551	-1.706547	.9099067
shfamw1	.0030017	.0095071	0.32	0.752	-.0156319	.0216353
shhlw1	.0103775	.0141593	0.73	0.464	-.0173742	.0381292
shjobw1	-.010105	.0099165	-1.02	0.308	-.029541	.009331
shrelaw1	.0000546	.0095661	0.01	0.995	-.0186946	.0188037
suprtw1	.0999707	.0455218	2.20	0.028	.0107496	.1891917
suchrw1	.0224317	.0297831	0.75	0.451	-.035942	.0808055
havmilsq	-1.68e-06	.0000133	-0.13	0.900	-.0000278	.0000245
radhlw1	0	(omitted)				
_cons	-18.64541	907.8458	-0.02	0.984	-1797.99	1760.7

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2sxlif

Classified	True		Total
	D	~D	
+	43	12	55
-	21	212	233
Total	64	224	288

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	67.19%
Specificity	$\Pr(- \sim D)$	94.64%
Positive predictive value	$\Pr(D +)$	78.18%
Negative predictive value	$\Pr(\sim D -)$	90.99%
False + rate for true ~D	$\Pr(+ \sim D)$	5.36%
False - rate for true D	$\Pr(- D)$	32.81%
False + rate for classified +	$\Pr(\sim D +)$	21.82%
False - rate for classified -	$\Pr(D -)$	9.01%
Correctly classified		88.54%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      288
number of covariate patterns =    288
    Pearson chi2(244) =    242.82
        Prob > chi2 =      0.5093

```

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-152.555	Log-Lik Full Model:	-77.749
D(234):	155.497	LR(43):	149.614
		Prob > LR:	0.000
McFadden's R2:	0.490	McFadden's Adj R2:	0.136
Maximum Likelihood R2:	0.405	Cragg & Uhler's R2:	0.620
McKelvey and Zavoina's R2:	0.766	Efron's R2:	0.518
Variance of y*:	14.056	Variance of error:	3.290
Count R2:	0.885	Adj Count R2:	0.484
AIC:	0.915	AIC*n:	263.497
BIC:	-1169.636	BIC':	93.894

```

*****
> *
*****
> *
*****
> *
*****
Full Nottingham Part 2 subscale models for male & females
> *
*****
Full main model for HP2sxlife for wave= 1
> *
*****
chunk 7 H1 test:Gender= 2 model Wave = 1 for HP2sxlife
> *
*****
> *
*****
> *
*****
18 Jun 2012 18:16:35
> *
*****
> *
*****

```

```

i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: bf15m != 0 predicts failure perfectly
      bf15m dropped and 11 obs not used

```

```

note: _Ieduc_8 omitted because of collinearity
note: radhlw1 omitted because of collinearity

```

Logistic regression	Number of obs	=	347
	LR chi2(50)	=	155.79
	Prob > chi2	=	0.0000
Log likelihood = -124.80461	Pseudo R2	=	0.3843

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1290605	.0254171	5.08	0.000	.0792439	.1788771
_Ieduc_2	-10.67087	962.4723	-0.01	0.991	-1897.082	1875.74
_Ieduc_3	-9.946262	962.4723	-0.01	0.992	-1896.357	1876.465
_Ieduc_4	-9.785405	962.4726	-0.01	0.992	-1896.197	1876.626
_Ieduc_5	-11.49393	962.4724	-0.01	0.990	-1897.905	1874.917
_Ieduc_6	-10.32295	962.4722	-0.01	0.991	-1896.734	1876.088
_Ieduc_7	-9.03504	962.4749	-0.01	0.993	-1895.451	1877.381
_Ieduc_8	0	(omitted)				
occ1w1	-2.600034	2.055585	-1.26	0.206	-6.628907	1.42884
occ2w1	-1.277677	2.051101	-0.62	0.533	-5.297761	2.742406
occ3w1	-1.369222	2.057018	-0.67	0.506	-5.400903	2.662459
occ4w1	-1.559837	2.12733	-0.73	0.463	-5.729327	2.609653
occ5w1	-2.429826	2.192792	-1.11	0.268	-6.727619	1.867967
occ6w1	-3.419242	2.325888	-1.47	0.142	-7.977899	1.139414
occ7w1	-2.504352	2.176283	-1.15	0.250	-6.769788	1.761083
occ8w1	-1.334187	2.100551	-0.64	0.525	-5.451192	2.782817
marrw11	-.7193048	1.925081	-0.37	0.709	-4.492394	3.053784
marrw12	.4856708	2.564006	0.19	0.850	-4.539688	5.51103
marrw13	-2.16757	1.867036	-1.16	0.246	-5.826893	1.491753
marrw15	-3.042565	2.275798	-1.34	0.181	-7.503047	1.417918
marrw16	-1.841276	2.263324	-0.81	0.416	-6.27731	2.594759
inc1w1	1.620964	1.976337	0.82	0.412	-2.252585	5.494512
inc2w1	1.094487	1.946444	0.56	0.574	-2.720473	4.909448
inc3w1	.8486289	1.968571	0.43	0.666	-3.009699	4.706957
inc4w1	1.499966	2.134492	0.70	0.482	-2.683562	5.683494
radhlw1	.007034	.0058778	1.20	0.231	-.0044862	.0185542
havmil	-.0000651	.0025878	-0.03	0.980	-.0051371	.0050069
avgcumdosew1	.599348	.3177091	1.89	0.059	-.0233504	1.222046
bf1	.0066905	.0314561	0.21	0.832	-.0549623	.0683434
bf4	-.1521557	.0440097	-3.46	0.001	-.2384131	-.0658983
bf9	-.0233371	.0265441	-0.88	0.379	-.0753625	.0286883
bf10	-.0152265	.0136272	-1.12	0.264	-.0419352	.0114823
bf11	-.0221841	.0445913	-0.50	0.619	-.1095814	.0652131
bf14	-.0000349	.0000708	-0.49	0.622	-.0001736	.0001039
bf15m	0	(omitted)				
bf20	-.0007465	.0262029	-0.03	0.977	-.0521033	.0506104
bf22	.0000643	.0000756	0.85	0.395	-.000084	.0002126
bf30	.0002306	.0003007	0.77	0.443	-.0003588	.00082
bf40	-.0231935	.1067574	-0.22	0.828	-.232434	.1860471
deaw1	.0559916	.1861244	0.30	0.764	-.3088055	.4207887
dvcew1	.4752968	3.360983	0.14	0.888	-6.112108	7.062702
sepaw1	.3375739	3.57474	0.09	0.925	-6.668788	7.343935
accdw1	-.4123297	.8114545	-0.51	0.611	-2.002751	1.178092
movew1	.7332906	.5919892	1.24	0.215	-.4269869	1.893568
illw1	.1110447	.3242585	0.34	0.732	-.5244903	.7465798
shfamw1	-.0101274	.0070668	-1.43	0.152	-.0239782	.0037233

shhlw1	-.0168708	.0106127	-1.59	0.112	-.0376714	.0039298
shjobw1	.0173829	.0076332	2.28	0.023	.002422	.0323437
shrelaw1	-.0004942	.0067313	-0.07	0.941	-.0136874	.012699
suprtw1	.0056448	.0100346	0.56	0.574	-.0140226	.0253123
suchrw1	-.0012594	.0144683	-0.09	0.931	-.0296168	.0270979
havmilsq	-2.25e-07	1.46e-06	-0.15	0.877	-3.08e-06	2.63e-06
radhlw1	0	(omitted)				
_cons	5.782713	962.4763	0.01	0.995	-1880.636	1892.202

Logistic model for HP2sxlif

Classified	True		Total
	D	~D	
+	57	20	77
-	37	233	270
Total	94	253	347

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

True D defined as HP2sxlif != 0

Sensitivity	$\Pr(+ D)$	60.64%
Specificity	$\Pr(- \sim D)$	92.09%
Positive predictive value	$\Pr(D +)$	74.03%
Negative predictive value	$\Pr(\sim D -)$	86.30%
False + rate for true ~D	$\Pr(+ \sim D)$	7.91%
False - rate for true D	$\Pr(- D)$	39.36%
False + rate for classified +	$\Pr(\sim D +)$	25.97%
False - rate for classified -	$\Pr(D -)$	13.70%
Correctly classified		83.57%

Logistic model for HP2sxlif, goodness-of-fit test

number of observations =	347
number of covariate patterns =	347
Pearson $\chi^2(296)$ =	311.56
Prob > χ^2 =	0.2559

Measures of Fit for logistic of HP2sxlif

Log-Lik Intercept Only:	-202.698	Log-Lik Full Model:	-124.805
D(293):	249.609	LR(50):	155.788
		Prob > LR:	0.000
McFadden's R2:	0.384	McFadden's Adj R2:	0.118
Maximum Likelihood R2:	0.362	Cragg & Uhler's R2:	0.525
McKelvey and Zavoina's R2:	0.605	Efron's R2:	0.422
Variance of y*:	8.326	Variance of error:	3.290
Count R2:	0.836	Adj Count R2:	0.394
AIC:	1.031	AIC*n:	357.609
BIC:	-1464.243	BIC':	136.679

```

922 .
923 . *-----Chunk 7 dose3 moderator => sex life impact-----
924 . title4 "Chunk 7 partly trimmed male model of dose=>HP2sxlife relationship in
> wave 1"

```

Chunk 7 partly trimmed male model of dose=>HP2sxlife relationship in wave 1

```

925 .      forvalues j=1/1 {
      2.          set more off
      3. di as input  "trimmed HP2sexlife main effects models wave 1 for H1 part 2
> with dose ns"
      4. di as input  "wave 1 male dose avgcumdosew`j' main effect not signif"
      5.          logit HP2sxlife age occ1w1-occ7w1 inclw1-inc4w1 bf4 bf40  ///
>          if gender==1
      6.                  estat class
      7.                  estat gof
      8.                  fitstat
      9. }

```

trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose ns
wave 1 male dose avgcumdosew1 main effect not signif

```

Iteration 0:  log likelihood = -171.51396
Iteration 1:  log likelihood = -118.07472
Iteration 2:  log likelihood = -110.61729
Iteration 3:  log likelihood = -110.3575
Iteration 4:  log likelihood = -110.35718
Iteration 5:  log likelihood = -110.35718

```

Logistic regression

Number of obs	=	340
LR chi2(14)	=	122.31
Prob > chi2	=	0.0000
Pseudo R2	=	0.3566

Log likelihood = **-110.35718**

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0941116	.0221002	4.26	0.000	.0507959	.1374272
occ1w1	-.8108243	.6947007	-1.17	0.243	-2.172413	.5507641
occ2w1	-.8508826	.7171286	-1.19	0.235	-2.256429	.5546637
occ3w1	-.8480358	.9624232	-0.88	0.378	-2.734351	1.038279
occ4w1	-.4031164	.7298235	-0.55	0.581	-1.833544	1.027311
occ5w1	-3.36185	1.50629	-2.23	0.026	-6.314124	-.4095757
occ6w1	-.2905401	1.302685	-0.22	0.824	-2.843755	2.262675
occ7w1	-.2498895	1.738151	-0.14	0.886	-3.656603	3.156824
inc1w1	1.792574	.9507668	1.89	0.059	-.0708952	3.656042
inc2w1	1.897351	.9299892	2.04	0.041	.0746052	3.720096
inc3w1	1.708189	.9374578	1.82	0.068	-.1291946	3.545573
inc4w1	1.397502	1.070212	1.31	0.192	-.7000754	3.49508
bf4	-.2058489	.0355202	-5.80	0.000	-.2754671	-.1362307
bf40	.2384671	.1033522	2.31	0.021	.0359004	.4410337
_cons	-5.837351	1.560717	-3.74	0.000	-8.896301	-2.778402

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	35	17	52
-	34	254	288
Total	69	271	340

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	50.72%
Specificity	$\Pr(- \sim D)$	93.73%
Positive predictive value	$\Pr(D +)$	67.31%
Negative predictive value	$\Pr(\sim D -)$	88.19%
False + rate for true ~D	$\Pr(+ \sim D)$	6.27%
False - rate for true D	$\Pr(- D)$	49.28%
False + rate for classified +	$\Pr(\sim D +)$	32.69%
False - rate for classified -	$\Pr(D -)$	11.81%
Correctly classified		85.00%

Logistic model for HP2sxlife, goodness-of-fit test

Measures of Fit for **logit** of **HP2sxl**life

```
926 .
927 . scalar MaineffhmcrMw1 = "age bf4 bf40"
928 .
929 . title "Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave
    > 1"
```



```
930 . title4 "h1 pt 2 wave 1 dose=> sex life impact on males"
```

```
h1 pt 2 wave 1 dose=> sex life impact on males
```

```
931 .      forvalues j=1/1 {
      2. set more off
      3. des occ5w1 inclw1 inc2w1 inc3w1
      4. di as input  "fully trimmed HP2sexlife main effects models wave 1 for H1
> part 2 with dose ns"
      5. di as input  "wave 1 male dose avgcumdosew`j' main effect not signif"
      6.      logit HP2sxlife age  bf4 bf40  shjobw`j' shrelaw`j' radhlw`j' if
> gender==1
      7.                  estat class
      8.                  estat gof
      9.                  fitstat
     10. }
```

variable name	storage type	display format	value label	variable label
occ5w1	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1986
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986

```
fully trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose ns
wave 1 male dose avgcumdosew1 main effect not signif
```

```
Iteration 0:  log likelihood = -171.51396
Iteration 1:  log likelihood = -121.19042
Iteration 2:  log likelihood = -114.60006
Iteration 3:  log likelihood = -114.41503
Iteration 4:  log likelihood = -114.41445
Iteration 5:  log likelihood = -114.41445
```

Logistic regression	Number of obs	=	340
	LR chi2(6)	=	114.20
	Prob > chi2	=	0.0000
Log likelihood = -114.41445	Pseudo R2	=	0.3329

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0617919	.0157391	3.93	0.000	.0309439	.09264
bf4	-.1966537	.0409434	-4.80	0.000	-.2769013	-.1164061
bf40	.2838331	.1042379	2.72	0.006	.0795305	.4881356
shjobw1	-.0050343	.0063951	-0.79	0.431	-.0175685	.0074999
shrelaw1	-.0020982	.0048927	-0.43	0.668	-.0116877	.0074913
radhlw1	.0066138	.0047502	1.39	0.164	-.0026965	.0159241
_cons	-3.247623	1.168417	-2.78	0.005	-5.537679	-.9575672

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	33	16	49
-	36	255	291
Total	69	271	340

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	47.83%
Specificity	$\Pr(- \sim D)$	94.10%
Positive predictive value	$\Pr(D +)$	67.35%
Negative predictive value	$\Pr(\sim D -)$	87.63%
False + rate for true ~D	$\Pr(+ \sim D)$	5.90%
False - rate for true D	$\Pr(- D)$	52.17%
False + rate for classified +	$\Pr(\sim D +)$	32.65%
False - rate for classified -	$\Pr(D -)$	12.37%
Correctly classified		84.71%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    335
Pearson chi2(328) =      293.15
Prob > chi2 =      0.9171

```

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

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-114.414
D(333):	228.829	LR(6):	114.199
		Prob > LR:	0.000
McFadden's R2:	0.333	McFadden's Adj R2:	0.292
Maximum Likelihood R2:	0.285	Cragg & Uhler's R2:	0.449
McKelvey and Zavoina's R2:	0.477	Efron's R2:	0.350
Variance of y*:	6.291	Variance of error:	3.290
Count R2:	0.847	Adj Count R2:	0.246
AIC:	0.714	AIC*n:	242.829
BIC:	-1712.210	BIC':	-79.225

932 .

933 . 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)

934 . scalar MainEffsxlifeMw1 = "age bf4 bf40 "

935 . scalar SigDosesxlifeMw1 = "no"

936 .

937 .

```
938 . forvalues j=1/1 {
      2. title4 "trimmed HP2sxlife main effects models wave `j' for H1 part 2 with
> dose ns"
      3. title4 "Wave `j' dose HPsxlife relationship but avgcumdosew`j': Dose not s
> ignif"
      4. }
```

trimmed HP2sxlife main effects models wave 1 for H1 part 2 with dose ns

Wave `j' dose HPsxlife relationship but avgcumdosew1: Dose not signif

```

939 .
940 . cap gen bf4Xd1= bf4*avgcumdosew1

941 . cap gen radhlw1Xd1 = radhlw1*avgcumdosew1

942 . cap gen ageXd1 = age*avgcumdosew1

943 .
944 . set more off

945 . des bf4

```

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

```

946 . forvalues j=1/1 {
      2.          sw, pr(.1):logistic HP2sxlife age bf4   ///
>          avgcumdosew`j' ageXd1 bf4Xd1 radhlw1Xd1 if gender==1, coef
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.6350 >= 0.1000 removing bf4Xd1
p = 0.4431 >= 0.1000 removing radhlw1Xd1
p = 0.1068 >= 0.1000 removing avgcumdosew1
p = 0.4455 >= 0.1000 removing ageXd1

```

Logistic regression	Number of obs	=	340
	LR chi2(2)	=	105.30
	Prob > chi2	=	0.0000
Log likelihood = -118.86164	Pseudo R2	=	0.3070

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0735516	.0151718	4.85	0.000	.0438154	.1032879
bf4	-.2011944	.0322322	-6.24	0.000	-.2643683	-.1380205
_cons	-3.058766	.9461336	-3.23	0.001	-4.913154	-1.204378

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	32	14	46
-	37	257	294
Total	69	271	340

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

Sensitivity	$\Pr(+ D)$	46.38%
Specificity	$\Pr(- \sim D)$	94.83%
Positive predictive value	$\Pr(D +)$	69.57%
Negative predictive value	$\Pr(\sim D -)$	87.41%
False + rate for true ~D	$\Pr(+ \sim D)$	5.17%
False - rate for true D	$\Pr(- D)$	53.62%
False + rate for classified +	$\Pr(\sim D +)$	30.43%
False - rate for classified -	$\Pr(D -)$	12.59%
Correctly classified		85.00%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    222
    Pearson chi2(219) =    215.06
        Prob > chi2 =      0.5625

```

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-118.862
D(337):	237.723	LR(2):	105.305
		Prob > LR:	0.000
McFadden's R2:	0.307	McFadden's Adj R2:	0.289
Maximum Likelihood R2:	0.266	Cragg & Uhler's R2:	0.419
McKelvey and Zavoina's R2:	0.435	Efron's R2:	0.320
Variance of y*:	5.825	Variance of error:	3.290
Count R2:	0.850	Adj Count R2:	0.261
AIC:	0.717	AIC*n:	243.723
BIC:	-1726.631	BIC':	-93.647

```

947 .
948 . scalar sxlifeModMw1 = "none"

949 . *xx male moderators: no main significant dose effect
950 . *xx no male moderators for sexlife impact
951 .
952 .
953 .
954 . title4 "H1 pt2 wave 1 female dose=> sexlife impact models"

-----
H1 pt2 wave 1 female dose=> sexlife impact models
-----

955 .
956 . *-----Chunk 7 dose3 moderator => sex life impact-----
> -
957 . di as input "chunk 7 female wave=3"
chunk 7 female wave=3

958 . title "Chunk 7 trimmed female model:" "dose and HP2sxlife relationship in wa
> ve 1"

*****
> *
*****
> *
*****
> *
*****
> *
*****
Chunk 7 trimmed female model:
> *
*****
dose and HP2sxlife relationship in wave 1
> *
*****
> *
*****
> *
*****
18 Jun 2012 18:16:49
> *
*****
> *
*****
> *

```

```

959 . * female models
960 .           forvalues j=1/1 {
      2.
961 . set more off
      3. des bf4 bf4m shfamw1 shrelaw1 avgcumdosew1
      4. title4 "trimmed HP2sexlife main effects models" "wave 1 for H1 part 2 wit
> h dose ns"
      5. title4 "wave 1 dose HP2sexlife relationship" "avgcumdosew`j' Dose not sig
> nif"
      6.           logit HP2sxlife age  radhlw`j' bf4 bf4m   ///
>           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)
shfamw1	double	%8.0g		Percentage of strains and hassles related to family in 1986
shrelaw1	double	%8.0g		Percentage of strains and hassles related to relationships in 1986
avgcumdosew1	double	%8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986

```
trimmed HP2sexlife main effects models
```

```
wave 1 dose HP2sexlife relationship
```

```

Iteration 0:  log likelihood = -207.32098
Iteration 1:  log likelihood = -149.84784
Iteration 2:  log likelihood = -145.01939
Iteration 3:  log likelihood = -144.95408
Iteration 4:  log likelihood = -144.95402
Iteration 5:  log likelihood = -144.95402

```

Logistic regression	Number of obs	=	362
	LR chi2(5)	=	124.73
	Prob > chi2	=	0.0000
Log likelihood = -144.95402	Pseudo R2	=	0.3008

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0771236	.0150604	5.12	0.000	.0476059	.1066414
radhlw1	.0062168	.0040945	1.52	0.129	-.0018083	.0142418
bf4	-.5739615	.185844	-3.09	0.002	-.9382091	-.2097139
bf4m	.3919975	.1717276	2.28	0.022	.0554176	.7285774
avgcumdosew1	.3818052	.2467519	1.55	0.122	-.1018197	.8654301
_cons	-7.066627	1.552843	-4.55	0.000	-10.11014	-4.023111

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	51	22	73
-	43	246	289
Total	94	268	362

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

Sensitivity	$\Pr(+ D)$	54.26%
Specificity	$\Pr(- \sim D)$	91.79%
Positive predictive value	$\Pr(D +)$	69.86%
Negative predictive value	$\Pr(\sim D -)$	85.12%
False + rate for true ~D	$\Pr(+ \sim D)$	8.21%
False - rate for true D	$\Pr(- D)$	45.74%
False + rate for classified +	$\Pr(\sim D +)$	30.14%
False - rate for classified -	$\Pr(D -)$	14.88%
Correctly classified		82.04%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      362
number of covariate patterns =    360
Pearson chi2(354) =      377.83
Prob > chi2 =      0.1837

```

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

Log-Lik Intercept Only:	-207.321	Log-Lik Full Model:	-144.954
D(356):	289.908	LR(5):	124.734
		Prob > LR:	0.000
McFadden's R2:	0.301	McFadden's Adj R2:	0.272
Maximum Likelihood R2:	0.291	Cragg & Uhler's R2:	0.427
McKelvey and Zavoina's R2:	0.451	Efron's R2:	0.348
Variance of y*:	5.995	Variance of error:	3.290
Count R2:	0.820	Adj Count R2:	0.309
AIC:	0.834	AIC*n:	301.908
BIC:	-1807.517	BIC':	-95.276

962 . scalar SigDoseSxlifeFw1 = "no"

963 . scalar MainEffsxlifeFw1 = "age bf4 bf4m"

964 . *----- constructing possible moderators

965 .

```
966 .      foreach var in bf4 bf4m shfamw1 shrelaw1 radhlw1 {
          2.          cap gen `var'Xd1 = `var'*avgcumdosew1
          3.          }
```

967 .

968 . scalar sxlifeModFw1="none"

969 . scalar SigDoseSxlifeFw1 = "none"

970 .

971 .

972 .

973 . *----- testing female moderators

974 . title "partly trimmed female moderator model of dose & HP2sxlife relationshi
> p in wv 1"

```
*****
> *
*****
> *
*****
> *
*****
> *
*****partly trimmed female moderator model of dose & HP2sxlife relationship in
> wv 1*****
*****
> *
*****
> *
*****
18 Jun 2012    18:16:50    ****
```

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

```
975 . * male models
976 .       forvalues j=1/1 {
      2. set more off
      3. des bf4 bf4m shfamw1 shrelaw1 avgcumdosew1
      4. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
      5. title "wave 1 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      6.       logit HP2sxlife age  radhlw`j' bf4 bf4m  ///
>       shrelaw`j' avgcumdosew`j' radhlw`j'Xd1 ///
>       bf4Xd1 shrelaw1Xd1  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)
shfamw1	double	%8.0g		Percentage of strains and hassles related to family in 1986
shrelaw1	double	%8.0g		Percentage of strains and hassles related to relationships in 1986
avgcumdosew1	double	%8.0g		wave 1 avg mean CS137 dose in mGy ending 12/31/1986

```
title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
18 Jun 2012
18:16:50
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests
> /h1pt2
Data file chwide16june2012.dta currently has 2386 variables and 703 obs
> ervations
```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****wave 1 dose HP2sexlife relationship but avgcumdosew1: Dose not signif****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *

```

```

Iteration 0:  log likelihood = -207.32098
Iteration 1:  log likelihood = -147.41511
Iteration 2:  log likelihood = -141.75413
Iteration 3:  log likelihood = -141.62542
Iteration 4:  log likelihood = -141.62494
Iteration 5:  log likelihood = -141.62494

```

```

Logistic regression                                Number of obs   =       362
                                                    LR chi2(9)      =      131.39
                                                    Prob > chi2     =       0.0000
Log likelihood = -141.62494                      Pseudo R2      =       0.3169

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0814535	.0153556	5.30	0.000	.0513571	.11155
radhlw1	.0024977	.0049558	0.50	0.614	-.0072155	.0122108
bf4	-.5313372	.1875606	-2.83	0.005	-.8989493	-.1637251
bf4m	.4140426	.1747902	2.37	0.018	.0714601	.7566252
shrelaw1	-.0104094	.0067432	-1.54	0.123	-.0236259	.0028071
avgcumdosew1	.8771287	.9794814	0.90	0.371	-1.04262	2.796877
radhlw1Xd1	.0106434	.0087424	1.22	0.223	-.0064914	.0277781
bf4Xd1	-.2197957	.1330334	-1.65	0.098	-.4805363	.040945
shrelaw1Xd1	.0233442	.0154714	1.51	0.131	-.0069791	.0536676
_cons	-7.515707	1.659151	-4.53	0.000	-10.76758	-4.26383

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	51	21	72
-	43	247	290
Total	94	268	362

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	54.26%
Specificity	$\Pr(- \sim D)$	92.16%
Positive predictive value	$\Pr(D +)$	70.83%
Negative predictive value	$\Pr(\sim D -)$	85.17%

False + rate for true ~D	$\Pr(+ \sim D)$	7.84%
False - rate for true D	$\Pr(- D)$	45.74%
False + rate for classified +	$\Pr(\sim D +)$	29.17%
False - rate for classified -	$\Pr(D -)$	14.83%

Correctly classified	82.32%
----------------------	---------------

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	362
number of covariate patterns =	361
Pearson chi2(351) =	368.67
Prob > chi2 =	0.2479

Measures of Fit for **logit** of HP2sxlife

Log-Lik Intercept Only:	-207.321	Log-Lik Full Model:	-141.625
D(352):	283.250	LR(9):	131.392
		Prob > LR:	0.000
McFadden's R2:	0.317	McFadden's Adj R2:	0.269
Maximum Likelihood R2:	0.304	Cragg & Uhler's R2:	0.446
McKelvey and Zavoina's R2:	0.536	Efron's R2:	0.365
Variance of y*:	7.085	Variance of error:	3.290
Count R2:	0.823	Adj Count R2:	0.319
AIC:	0.838	AIC*n:	303.250
BIC:	-1790.609	BIC':	-78.367

```

977 . // trimming further
978 . title "fully female moderator model of dose & HP2sxlife relationship in wv 1
> "

*****
> *
*****
> *
*****
> *
*****
> *
*****fully female moderator model of dose & HP2sxlife relationship in wv 1****
> *
*****
> *
*****
> *
*****
> *
*****18 Jun 2012 18:16:51 ****
> *
*****
> *
*****
> *

979 .
980 .
981 . * female models
982 . set more off

983 . forvalues j=1/1 {
2. des bf4 bf4m shfamw1 shrelaw1 avgcumdosew1
3. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
4. title "wave 1 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
5. logit HP2sxlife age radhlw`j' bf4 bf4m ///
shrelaw1 avgcumdosew`j' ///
> shrelaw1Xd1 if gender==2
6. estat class
7. estat gof
8. fitstat
9. }

```

```
title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
18 Jun 2012
18:16:51
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests
> /h1pt2
Data file chwide16june2012.dta currently has 2386 variables and 703 obs
> ervations
```

> *

Iteration 0: log likelihood = **-207.32098**
 Iteration 1: log likelihood = **-148.73094**
 Iteration 2: log likelihood = **-143.96367**
 Iteration 3: log likelihood = **-143.91142**
 Iteration 4: log likelihood = **-143.91139**
 Iteration 5: log likelihood = **-143.91139**

Logistic regression

Number of obs = **362**
 LR chi2(7) = **126.82**
 Prob > chi2 = **0.0000**
 Pseudo R2 = **0.3059**

Log likelihood = **-143.91139**

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0780855	.0151068	5.17	0.000	.0484767	.1076944
radhlw1	.0057692	.0041216	1.40	0.162	-.0023091	.0138474
bf4	-.5774463	.1888057	-3.06	0.002	-.9474987	-.2073939
bf4m	.3915506	.1745706	2.24	0.025	.0493985	.7337026
shrelaw1	-.0078788	.0061361	-1.28	0.199	-.0199053	.0041477
avgcumdosew1	.0233678	.3583816	0.07	0.948	-.6790473	.7257829
shrelaw1Xd1	.0143198	.0116222	1.23	0.218	-.0084592	.0370989
_cons	-6.851526	1.575045	-4.35	0.000	-9.938557	-3.764495

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	53	23	76
-	41	245	286
Total	94	268	362

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

Sensitivity	Pr(+ D)	56.38%
Specificity	Pr(- ~D)	91.42%
Positive predictive value	Pr(D +)	69.74%
Negative predictive value	Pr(~D -)	85.66%
False + rate for true ~D	Pr(+ ~D)	8.58%
False - rate for true D	Pr(- D)	43.62%
False + rate for classified +	Pr(~D +)	30.26%
False - rate for classified -	Pr(D -)	14.34%
Correctly classified		82.32%

Logistic model for HP2sxlife, goodness-of-fit test

```
number of observations =      362
number of covariate patterns =    361
Pearson chi2(353) =      375.36
Prob > chi2 =      0.1978
```

Measures of Fit for logit of HP2sxlife

Log-Lik Intercept Only:	-207.321	Log-Lik Full Model:	-143.911
D(354):	287.823	LR(7):	126.819
		Prob > LR:	0.000
McFadden's R2:	0.306	McFadden's Adj R2:	0.267
Maximum Likelihood R2:	0.296	Cragg & Uhler's R2:	0.433
McKelvey and Zavoina's R2:	0.465	Efron's R2:	0.353
Variance of y*:	6.146	Variance of error:	3.290
Count R2:	0.823	Adj Count R2:	0.319
AIC:	0.839	AIC*n:	303.823
BIC:	-1797.819	BIC':	-85.578

```
984 . * female models
985 .     forvalues j=1/1 {
      2. des bf4 bf4m shfamw1 shrelaw1 avgcumdosew1
      3. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
      4. title "wave 1 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      5.     logit HP2sxlife age  radhlw`j' bf4 bf4m    ///
>         shrelaw1 shfamw`j'    ///
>         if gender==2
      6.         estat class
      7.         estat gof
      8.         fitstat
      9. }
```

```
title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
18 Jun 2012
18:16:53
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests
> /h1pt2
Data file chwide16june2012.dta currently has 2386 variables and 703 obs
> ervations
```

> *

```

Iteration 0:  log likelihood = -207.32098
Iteration 1:  log likelihood = -151.03193
Iteration 2:  log likelihood = -146.24555
Iteration 3:  log likelihood = -146.19381
Iteration 4:  log likelihood = -146.19378
Iteration 5:  log likelihood = -146.19378

```

Logistic regression

```

Number of obs   =      362
LR chi2(6)      =     122.25
Prob > chi2     =      0.0000
Pseudo R2      =      0.2948

```

Log likelihood = **-146.19378**

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0785876	.0150203	5.23	0.000	.0491483	.1080268
radhlw1	.0058723	.004062	1.45	0.148	-.0020891	.0138337
bf4	-.5874305	.1868633	-3.14	0.002	-.9536758	-.2211852
bf4m	.3963155	.172212	2.30	0.021	.0587862	.7338448
shrelaw1	-.0014364	.0051848	-0.28	0.782	-.0115983	.0087256
shfamw1	-.0015628	.0050062	-0.31	0.755	-.0113747	.0082491
_cons	-6.829393	1.564771	-4.36	0.000	-9.896289	-3.762497

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	50	22	72
-	44	246	290
Total	94	268	362

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	53.19%
Specificity	$\Pr(- \sim D)$	91.79%
Positive predictive value	$\Pr(D +)$	69.44%
Negative predictive value	$\Pr(\sim D -)$	84.83%

False + rate for true ~D	$\Pr(+ \sim D)$	8.21%
False - rate for true D	$\Pr(- D)$	46.81%
False + rate for classified +	$\Pr(\sim D +)$	30.56%
False - rate for classified -	$\Pr(D -)$	15.17%

Correctly classified	81.77%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	362
number of covariate patterns =	360
Pearson chi2(353) =	374.57
Prob > chi2 =	0.2058

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

Log-Lik Intercept Only:	-207.321	Log-Lik Full Model:	-146.194
D(355):	292.388	LR(6):	122.254
		Prob > LR:	0.000
McFadden's R2:	0.295	McFadden's Adj R2:	0.261
Maximum Likelihood R2:	0.287	Cragg & Uhler's R2:	0.420
McKelvey and Zavoina's R2:	0.446	Efron's R2:	0.339
Variance of y*:	5.936	Variance of error:	3.290
Count R2:	0.818	Adj Count R2:	0.298
AIC:	0.846	AIC*n:	306.388
BIC:	-1799.146	BIC':	-86.905

```
986 .
987 . scalar MainEffsxlifeFw1 = "age radhlw1 bf4 bf4m"

988 . scalar SigDoseSxlifeFw1="no"

989 . scalar SxLifeModFw1 = "no"

990 . * xx female main effects model: no sign dose main effect
991 . * xx 6 signif main effects
992 . * xx no moderator effects significant
993 .
994 . title4 "h1 pt 2 wave 1 dose-> sexlife sexlife mediator impact models"
```

```
h1 pt 2 wave 1 dose-> sexlife sexlife mediator impact models
```

```

995 .
996 . di as input "testing possible sex life mediator effects for males"
      testing possible sex life mediator effects for males

997 .
998 . * age is a mediating effect for males for Dose=> sex life for men
999 . 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)

```

1000 . glm age avgcumdosew1 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1331.608**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	148.5632
Deviance = 50214.37624	(1/df) Deviance	=	148.5632
Pearson = 50214.37624	(1/df) Pearson	=	148.5632

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

	<u>AIC</u>	=	7.844753
Log likelihood = -1331.607976	<u>BIC</u>	=	48244.19

age	OIM			P> z	[95% Conf. Interval]	
	Coef.	Std. Err.	z			
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
1001 . glm HP2sxlife age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =    287.05
Iteration 2:  deviance =   282.9134
Iteration 3:  deviance =   282.8157
Iteration 4:  deviance =   282.8156
Iteration 5:  deviance =   282.8156
```

```
Generalized linear models                      No. of obs      =       340
Optimization      :  MQL Fisher scoring        Residual df      =       338
                   (IRLS EIM)                 Scale parameter =         1
Deviance          =   282.8156218              (1/df) Deviance =   .8367326
Pearson           =   327.5643783              (1/df) Pearson  =   .9691254
```

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

```
BIC = -1687.368
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0532907	.0067666	7.88	0.000	.0400283	.0665531
_cons	-3.620299	.3741324	-9.68	0.000	-4.353585	-2.887013

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

```
1002 .
1003 .
1004 . des illw1
```

variable name	storage type	display format	value label	variable label
illw1	double	%8.0g		Total number of illnesses experienced in time period 1976-1986

```
1005 . glm illw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -151.48261
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.1435742
Deviance = 48.52808533	(1/df) Deviance	=	.1435742
Pearson = 48.52808533	(1/df) Pearson	=	.1435742

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

	<u>AIC</u>	=	.9028389
Log likelihood = -151.4826069	<u>BIC</u>	=	-1921.656

illw1	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew1	.0087277	.0123318	0.71	0.479	-.0154423	.0328976	
_cons	.0962541	.0212201	4.54	0.000	.0546635	.1378446	

```
1006 . glm HP2sxlife illw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 342.7406
Iteration 2: deviance = 342.5208
Iteration 3: deviance = 342.5207
Iteration 4: deviance = 342.5207
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 342.5207329	(1/df) Deviance	=	1.013375
Pearson = 340.1346783	(1/df) Pearson	=	1.006316

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

	BIC	=	-1627.663
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illwl	.1374179	.1941211	0.71	0.479	-.2430524	.5178882
_cons	-.8459321	.0807352	-10.48	0.000	-1.00417	-.6876941

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

1007 .
1008 . des radhlwl

variable name	storage type	display format	value label	variable label
radhlwl	double	%8.0g		how much believed personal health is affected by radiation in 1986

1009 . glm radhlwl avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1710.3417**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1378.645
Deviance = 465981.8893	(1/df) Deviance	=	1378.645
Pearson = 465981.8893	(1/df) Pearson	=	1378.645

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

	<u>AIC</u>	=	10.0726
Log likelihood = -1710.341694	<u>BIC</u>	=	464011.7

radhlwl	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	2.398285	1.208412	1.98	0.047	.0298407	4.766729
_cons	44.66477	2.079384	21.48	0.000	40.58925	48.74029

```
1010 . glm HP2sxlife radhlw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 314.3547
Iteration 2:  deviance = 313.2652
Iteration 3:  deviance = 313.2621
Iteration 4:  deviance = 313.2621
```

```
Generalized linear models          No. of obs      =       340
Optimization      : MQL Fisher scoring      Residual df    =       338
                    (IRLS EIM)              Scale parameter =         1
Deviance          = 313.2620862             (1/df) Deviance = .9268109
Pearson           = 338.905649              (1/df) Pearson  = 1.002679
```

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

```
BIC                                     = -1656.922
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.0115464	.0020885	5.53	0.000	.007453	.0156398
_cons	-1.434416	.1399661	-10.25	0.000	-1.708745	-1.160088

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

```
1011 .
1012 .
1013 . des bf4
```

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

```
1014 . glm bf4 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1026.9659
```

```
Generalized linear models          No. of obs      =       340
Optimization      : ML              Residual df    =       338
Scale parameter = 24.75428
Deviance          = 8366.946191      (1/df) Deviance = 24.75428
Pearson           = 8366.946191      (1/df) Pearson  = 24.75428
```

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

Log likelihood	= -1026.965868	<u>AIC</u>	= 6.05274
		<u>BIC</u>	= 6396.763

	OIM					
bf4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.1031788	.161925	-0.64	0.524	-.4205461	.2141884
_cons	12.54134	.2786337	45.01	0.000	11.99523	13.08746

```
1015 . 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

	EIM					
HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1431725	.0149643	-9.57	0.000	-.172502	-.1138431
_cons	.7780696	.180124	4.32	0.000	.425033	1.131106

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

```
1016 .
1017 . des bf4m
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1018 . glm bf4m avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1060.6611
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	30.18079
Deviance	= 10201.10756	(1/df) Deviance	=	30.18079
Pearson	= 10201.10756	(1/df) Pearson	=	30.18079
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	6.250948
Log likelihood	= -1060.661115	<u>BIC</u>	=	8230.924

bf4m	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew1	-.0953671	.1787945	-0.53	0.594	-.4457979	.2550637
_cons	20.35858	.307662	66.17	0.000	19.75557	20.96159

```
1019 . 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					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
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.)

1020 .

1021 . des shrelaw1

variable name	storage type	display format	value label	variable label
shrelaw1	double	%8.0g		Percentage of strains and hassles related to relationships in 1986

1022 . glm shrelaw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1715.4166

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1420.421
Deviance = 480102.3567	(1/df) Deviance	=	1420.421
Pearson = 480102.3567	(1/df) Pearson	=	1420.421
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	AIC	=	10.10245
Log likelihood = -1715.416629	BIC	=	478132.2

shrelaw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.0649405	1.226584	-0.05	0.958	-2.469002	2.339121
_cons	29.57199	2.110654	14.01	0.000	25.43518	33.7088

```
1023 . glm HP2sxlife shrelaw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =  341.3096
Iteration 2:  deviance =  341.0889
Iteration 3:  deviance =  341.0888
Iteration 4:  deviance =  341.0888
```

```
Generalized linear models                      No. of obs      =       340
Optimization      :  MQL Fisher scoring        Residual df     =       338
                  (IRLS EIM)                  Scale parameter =         1
Deviance          =  341.0887685              (1/df) Deviance =  1.009138
Pearson           =  340.3303886              (1/df) Pearson  =  1.006895
```

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

```
BIC                                     = -1629.095
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw1	.0027916	.00202	1.38	0.167	-.0011676	.0067508
_cons	-.9180819	.1010594	-9.08	0.000	-1.116155	-.7200091

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

```
1024 .
1025 . des shfamw1
```

variable name	storage type	display format	value label	variable label
shfamw1	double	%8.0g		Percentage of strains and hassles related to family in 1986

```
1026 . glm shfamw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1722.3986
```

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1524.9
Deviance = 513891.1861	(1/df) Deviance	=	1524.9
Pearson = 513891.1861	(1/df) Pearson	=	1524.9

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

	<u>AIC</u>	=	10.17344
Log likelihood = -1722.398621	<u>BIC</u>	=	511927.8

shfamw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.8322929	1.270907	-0.65	0.513	-3.323226	1.65864
_cons	38.72924	2.190054	17.68	0.000	34.43681	43.02167

```
1027 . glm HP2sxlife shfamw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 339.011
Iteration 2: deviance = 338.8015
Iteration 3: deviance = 338.8014
Iteration 4: deviance = 338.8014
```

Generalized linear models	No. of obs	=	339
Optimization : ML Fisher scoring	Residual df	=	337
(IRLS EIM)	Scale parameter	=	1
Deviance = 338.8013645	(1/df) Deviance	=	1.005345
Pearson = 339.2776273	(1/df) Pearson	=	1.006759

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

	BIC	=	-1624.561
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw1	.0019797	.0019787	1.00	0.317	-.0018986	.0058579
_cons	-.9179132	.1113818	-8.24	0.000	-1.136218	-.6996088

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

```

1028 .
1029 . scalar sxlifeMedMw1 = "radhlw1"

1030 .
1031 . title4 "female impact models mediator search"

```

female impact models mediator search

```

1032 .
1033 . * age is a mediating effect for females for Dose=> sex life for women
1034 . glm age avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.325**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.455
Deviance = 49260.25928	(1/df) Deviance	=	136.455
Pearson = 49260.25928	(1/df) Pearson	=	136.455

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

	<u>AIC</u>	=	7.759366
Log likelihood = -1406.325011	<u>BIC</u>	=	47132.38

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```
1035 . 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      :  MQL 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.)

```
1036 .
1037 . * illness is a mediating effect for females = > sex life for men
1038 . des illw1
```

variable name	storage type	display format	value label	variable label
illw1	double	%8.0g		Total number of illnesses experienced in time period 1976-1986

```
1039 . glm illw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -259.70777
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.2462383
Deviance = 88.89203958	(1/df) Deviance	=	.2462383
Pearson = 88.89203958	(1/df) Pearson	=	.2462383

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

Log likelihood = -259.7077741	AIC	=	1.441916
	BIC	=	-2038.987

illw1	OIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
avgcumdosew1	.0655142	.0474789	1.38	0.168	-.0275426	.1585711
_cons	.1570822	.0305304	5.15	0.000	.0972436	.2169207

```
1040 . glm HP2sxlife illw1 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 412.1945
Iteration 2: deviance = 411.6441
Iteration 3: deviance = 411.6439
Iteration 4: deviance = 411.6439
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 411.6438998	(1/df) Deviance	=	1.140288
Pearson = 362.6903423	(1/df) Pearson	=	1.004682

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

BIC	=	-1716.236
-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw1	.257456	.1453235	1.77	0.076	-.0273728	.5422847
_cons	-.6974831	.0815339	-8.55	0.000	-.8572865	-.5376797

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

```

1041 .
1042 . *----- this may be important -----
1043 . * radhlw1 can be a mediating factor for females in wave 1 for sxlife
1044 . des radhlw1

```

variable name	storage type	display format	value label	variable label
radhlw1	double	%8.0g		how much believed personal health is affected by radiation in 1986

```

1045 . glm radhlw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1821.9477**

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	360
	Scale parameter	=	1385.301
Deviance = 498708.3025	(1/df) Deviance	=	1385.301
Pearson = 498708.3025	(1/df) Pearson	=	1385.301
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	10.07706
Log likelihood = -1821.947718	<u>BIC</u>	=	496587.3

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.789972	3.562254	1.06	0.287	-3.191917	10.77186
_cons	55.44948	2.293757	24.17	0.000	50.9538	59.94516

```
1046 . glm HP2sxlife radhlw1 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 401.9956
Iteration 2:  deviance = 401.6315
Iteration 3:  deviance = 401.6315
Iteration 4:  deviance = 401.6315
```

```
Generalized linear models               No. of obs      =       362
Optimization      :  MQL Fisher scoring  Residual df      =       360
                    (IRLS EIM)           Scale parameter =         1
Deviance          = 401.6314992          (1/df) Deviance = 1.115643
Pearson           = 362.7806158          (1/df) Pearson  = 1.007724
```

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

```
BIC                                     = -1719.36
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.0070351	.0020921	3.36	0.001	.0029347	.0111355
_cons	-1.06549	.1496137	-7.12	0.000	-1.358728	-.7722525

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

```
1047 . *-----
> --
1048 .
1049 . des bf4    // soma recentered
```

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

```

1050 . * bf4 is a mediting effect for females for Dose=> sex life for women
1051 . glm bf4 avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1109.0162**

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
		Scale parameter	=	26.52082
Deviance	= 9574.015672	(1/df) Deviance	=	26.52082
Pearson	= 9574.015672	(1/df) Pearson	=	26.52082
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]
		<u>AIC</u>	=	6.121302
Log likelihood	= -1109.016226	<u>BIC</u>	=	7446.136

bf4	OIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```

1052 . glm HP2sxlife bf4 if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **344.0399**
 Iteration 2: deviance = **342.6827**
 Iteration 3: deviance = **342.6686**
 Iteration 4: deviance = **342.6686**
 Iteration 5: deviance = **342.6686**

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	361
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 342.6686152	(1/df) Deviance	=	.9492205
Pearson	= 336.3540555	(1/df) Pearson	=	.9317287
Variance function:	V(u) = u*(1-u)			[Bernoulli]
Link function	: g(u) = invnorm(u)			[Probit]
		<u>BIC</u>	=	-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.)

1053 .

1054 . des bf4m // soma recentered

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

1055 . * bf4m is a possible mediating effect for female sex life

1056 . glm bf4m avgcumdosew1 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1140.521**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	31.548
Deviance = 11388.82943	(1/df) Deviance	=	31.548
Pearson = 11388.82943	(1/df) Pearson	=	31.548

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

	<u>AIC</u>	=	6.294882
Log likelihood = -1140.521046	<u>BIC</u>	=	9260.95

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.563541	.5374133	-2.91	0.004	-2.616852	-.5102303
_cons	18.82212	.3455741	54.47	0.000	18.1448	19.49943

```
1057 . 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                 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) = invnorm(u)                 [Probit]
```

```
BIC = -1772.262
```

HP2sxlife	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
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.)

```
1058 .
```

```
1059 . des shfamw1
```

variable name	storage type	display format	value label	variable label
shfamw1	double	%8.0g		Percentage of strains and hassles related to family in 1986

```
1060 . glm shfamw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1820.2144
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1334.587
Deviance = 481786.0787	(1/df) Deviance	=	1334.587
Pearson = 481786.0787	(1/df) Pearson	=	1334.587

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

	<u>AIC</u>	=	10.03975
Log likelihood = -1820.214442	<u>BIC</u>	=	479658.2

shfamw1	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew1	2.325224	3.495393	0.67	0.506	-4.525621	9.176069	
_cons	34.91682	2.24765	15.53	0.000	30.5115	39.32213	

```
1061 . glm HP2sxlife shfamw1 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 415.7461
Iteration 2: deviance = 415.0916
Iteration 3: deviance = 415.0914
Iteration 4: deviance = 415.0914
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 415.0913862	(1/df) Deviance	=	1.149838
Pearson = 362.9739265	(1/df) Pearson	=	1.005468

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

	BIC	=	-1712.788
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw1	.0007609	.0020813	0.37	0.715	-.0033182	.0048401
_cons	-.6739948	.1071104	-6.29	0.000	-.8839274	-.4640622

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

```
1062 .
1063 . des shrelaw1
```

variable name	storage type	display format	value label	variable label
shrelaw1	double	%8.0g		Percentage of strains and hassles related to relationships in 1986

```
1064 . glm shrelaw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1801.2674**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1202.293
Deviance = 434027.9437	(1/df) Deviance	=	1202.293
Pearson = 434027.9437	(1/df) Pearson	=	1202.293

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

	<u>AIC</u>	=	9.935358
Log likelihood = -1801.267425	<u>BIC</u>	=	431900.1

shrelaw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	5.240218	3.317628	1.58	0.114	-1.262215	11.74265
_cons	26.01592	2.133342	12.19	0.000	21.83464	30.19719

```
1065 . glm HP2sxlife shrelaw1 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 414.3957
Iteration 2:  deviance = 413.7847
Iteration 3:  deviance = 413.7844
Iteration 4:  deviance = 413.7844
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  MQL Fisher scoring                  Residual df     =       361
                   (IRLS EIM)                           Scale parameter =        1
Deviance          = 413.7844342                         (1/df) Deviance = 1.146217
Pearson           = 362.9072137                         (1/df) Pearson  = 1.005283
```

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

```
BIC = -1714.095
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw1	.002446	.0021561	1.13	0.257	-.0017799	.0066718
_cons	-.7168064	.0987075	-7.26	0.000	-.9102696	-.5233433

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

```
1066 .
```

```
1067 . glm aborw1 avgcumdosew1 if gender==2, fam(pois) link(log)
```

```
Iteration 0:  log likelihood = -294.95486
Iteration 1:  log likelihood = -274.67418
Iteration 2:  log likelihood = -274.64155
Iteration 3:  log likelihood = -274.64155
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  ML                                  Residual df     =       361
Deviance          = 418.9504185                         Scale parameter =        1
Pearson           = 1079.525061                        (1/df) Deviance = 1.160527
                                                         (1/df) Pearson  = 2.990374
```

```
Variance function: V(u) = u                            [Poisson]
Link function     : g(u) = ln(u)                        [Log]
```

```
Log likelihood    = -274.6415467                        AIC              = 1.524196
                                                         BIC              = -1708.929
```

aborw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.0974558	.154214	0.63	0.527	-.204798	.3997097
_cons	-1.333588	.1156098	-11.54	0.000	-1.560179	-1.106997

1068 . glm HP2sxlife aborw1 if gender==2, fam(bin) link(probit) irls scale(dev)

Iteration 1: deviance = **414.3147**
Iteration 2: deviance = **413.5468**
Iteration 3: deviance = **413.545**
Iteration 4: deviance = **413.545**
Iteration 5: deviance = **413.545**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 413.5449635	(1/df) Deviance	=	1.145554
Pearson = 362.1757599	(1/df) Pearson	=	1.003257

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

BIC = **-1714.334**

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
aborw1	-.1290317	.1159726	-1.11	0.266	-.3563338	.0982703
_cons	-.615959	.0802001	-7.68	0.000	-.7731484	-.4587696

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

1069 .

```

1070 . title4 "h1 pt2 wave 1 sex life impact summary matrix construction"
      _____
      h1 pt2 wave 1 sex life impact summary matrix construction
      _____

1071 .
1072 . *xx summary of mediating effects:  age and illness mediate sex life for men
1073 . *                                age illness radhlw1 bf4 bf4m (soma) medi
      > ate sex life for women
1074 .
1075 . scalar SigDoseMEhmcrW1 = "no"

1076 . scalar MaineffhmcrMw1 = "age bf4 bf40"

1077 .
1078 . scalar MainEffsxlifeFw1 = "age radhlw1 bf4 bf4m"

1079 . scalar SigDoseSxlifeFw1="no"

1080 . scalar SxLifeModFw1 = "no"

1081 . scalar sxlifeModMw1 = "none"

1082 . * xx female main effects model scalar SigDoseSxlifeFw1 = "no"
1083 . scalar MainEffsxlifeFw1 = "age bf4 bf4m"

1084 . scalar sxlifeMedMw1 = "age illw1"

1085 . scalar sxlifeMedFw1 = "age illw1 radhlw1 bf4 bf4m"

1086 . scalar sxlifeMedMw1 = "radhlw1"

1087 .
1088 . *--- summary matrix construction
1089 .
1090 .   matrix define  sxlifeMw1 = J(1,8, 0)

```

```

1091 .      matrix define  sxlifeFw1 = J(1,8, 0)

1092 . matrix colnames  sxlifeMw1=  hypnum ptnum wave gender medsig numMA sig numMed
    > sig numMed

1093 .      matrix colnames  sxlifeFw1=  hypnum ptnum wave gender medsig numMA sig numMod
    > g numModsig numMed

1094 .      matrix define  sxlifeMw1= (1, 2, 1, 1, 0, 3, 0, 1 )

1095 .      matrix define  sxlifeFw1= (1, 2, 1, 2, 0, 4, 0, 5)

1096 .      matrix rowname  sxlifeMw1 =  sxlifeMw1

1097 .      matrix rowname  sxlifeFw1 =  sxlifeFw1

1098 .      matlist  sxlifeMw1

    > 6      |      c1      c2      c3      c4      c5      c
    >      |      c7      c8
    -----+-----
    >      |
    > sxlifeMw1 |      1      2      1      1      0
    > 3      |      0      1
    >      |

1099 .      matlist  sxlifeFw1

    > 6      |      c1      c2      c3      c4      c5      c
    >      |      c7      c8
    -----+-----
    >      |
    > sxlifeFw1 |      1      2      1      2      0
    > 4      |      0      5
    >      |

1100 .      matrix define H1pt2w1 = ( wkMw1 \ wkFw1 \ hmcrMw1 \ hmcrFw1 \ sp
    > Mw1 \ spFw1 \ prbfamMw1 \ prbfamFw1 \ sxlifeMw1 \ sxlifeFw1 )

```

```

1101 .
1102 .      matlist H1pt2w1

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 1	1	2					
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 2	0	2					
	spMw1	1	2	1	1	1	
> 2	2	1					
	spFw1	1	2	1	2	0	
> 5	0	2					
	prbfamMw1	1	2	1	1	0	
> 2	0	0					
	prbfamFw1	1	2	1	2	0	
> 3	0	2					
	sxlifeMw1	1	2	1	1	0	
> 3	0	1					
	sxlifeFw1	1	2	1	2	0	
> 4	0	5					

```

1103 .      matrix colnames H1pt2w1 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed

```

```

1104 .      matrix rownames H1pt2w1 =  wkMw1 wkFw1 hmcMw1 hmcFw1 spMw1 spFw1 p
> rbfhmMw1 prbfhmFw1

```

```

1105 .      matlist H1pt2w1

```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2	0	1					
	wkFw1	1	2	1	2	0	
> 1	1	2					
	hmcMw1	1	2	1	1	0	
> 2	0	1					
	hmcFw1	1	2	1	2	0	
> 2	0	2					
	spMw1	1	2	1	1	1	

```

> 2      2      1
      spFw1 |      1      2      1      2      0
> 5      0      2
      prbfhmMw1 |      1      2      1      1      0
> 2      0      0
      prbfhmFw1 |      1      2      1      2      0
> 3      0      2
      prbfhmFw1 |      1      2      1      1      0
> 3      0      1
      prbfhmFw1 |      1      2      1      2      0
> 4      0      5

```

```

1106 .
1107 .
1108 .
1109 .
1110 . *===== Chunk 8      Dose => interests and Hobbies relationship
1111 .
1112 . title " 6. H1 wave 1 part2  Dose-Interest and Hobbies impact"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****      6. H1 wave 1 part2  Dose-Interest and Hobbies impact      ****
> *
*****
> *
*****
> *
*****
> *
*****      18 Jun 2012      18:17:37      ****
> *
*****
> *
*****
> *

```

```

1113 .
1114 .
1115 . * Chunk 8 ---male models
1116 . forvalues j=1/1 {
      2. set more off
      3.
1117 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1118 .   foreach var in HP2inthob {
      5.       forvalues k=1/2 {
      6.   local wlb bf1 bf4 bf9 bf10 bf11 bf14 bf15m bf20 bf22 bf30 bf40
      7.
1119 . 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 radhlw1 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


```

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

```

Model for gender==1 and wave == 1

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: occ6w1 != 0 predicts failure perfectly
 occ6w1 dropped and 4 obs not used

note: occ7w1 != 0 predicts failure perfectly
 occ7w1 dropped and 4 obs not used

note: marrw15 != 0 predicts success perfectly
 marrw15 dropped and 1 obs not used

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

note: dvcew1 != 0 predicts failure perfectly
 dvcew1 dropped and 2 obs not used

note: sepaw1 != 0 predicts failure perfectly
 sepaw1 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
 note: marrw16 omitted because of collinearity
 note: radhlw1 omitted because of collinearity
 convergence not achieved

Logistic regression	Number of obs	=	284
	LR chi2(40)	=	100.41
	Prob > chi2	=	0.0000
Log likelihood = -55.819677	Pseudo R2	=	0.4735

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1670729	.0496836	3.36	0.001	.0696948	.2644509
_Ieduc_2	-3.680581	2.320262	-1.59	0.113	-8.228211	.8670494
_Ieduc_3	-.4101129	.8396848	-0.49	0.625	-2.055865	1.235639
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.2315388	.8579156	-0.27	0.787	-1.913023	1.449945
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w1	-.855187	2.512009	-0.34	0.734	-5.778634	4.06826
occ2w1	-.8206155	2.564147	-0.32	0.749	-5.846251	4.20502
occ3w1	.4752119	2.731393	0.17	0.862	-4.87822	5.828644
occ4w1	-.0629245	2.648929	-0.02	0.981	-5.254729	5.12888
occ5w1	.1433339	2.754114	0.05	0.958	-5.254631	5.541299
occ6w1	0	(omitted)				
occ7w1	0	(omitted)				
occ8w1	2.572986	2.905992	0.89	0.376	-3.122655	8.268626
marrw11	13.32407	13699.24	0.00	0.999	-26836.69	26863.34
marrw12	14.0947	13699.24	0.00	0.999	-26835.93	26864.11
marrw13	12.02184	13699.24	0.00	0.999	-26838	26862.04
marrw15	0	(omitted)				
marrw16	0	(omitted)				
inc1w1	-2.316757	2.703555	-0.86	0.391	-7.615628	2.982114
inc2w1	-1.011499	2.582483	-0.39	0.695	-6.073072	4.050074
inc3w1	-1.18772	2.503558	-0.47	0.635	-6.094604	3.719164
inc4w1	-3.273623	3.286978	-1.00	0.319	-9.715981	3.168734
radhlw1	.0108481	.0098238	1.10	0.269	-.0084061	.0301023
havmil	.011552	.0121868	0.95	0.343	-.0123338	.0354378
avgcumdosew1	-.0246271	.287731	-0.09	0.932	-.5885695	.5393153
bf1	-1.705805	342.4811	-0.00	0.996	-672.9563	669.5447
bf4	-.2162507	.0773979	-2.79	0.005	-.3679478	-.0645536
bf9	-.0313278	.0435662	-0.72	0.472	-.116716	.0540605
bf10	-.058867	.0329385	-1.79	0.074	-.1234253	.0056913
bf11	-.0066494	.0862166	-0.08	0.939	-.1756309	.162332
bf14	-.0001753	.0001131	-1.55	0.121	-.0003971	.0000464
bf15m	0	(omitted)				
bf20	1.703694	342.481	0.00	0.996	-669.5468	672.9542
bf22	.0001385	.0001388	1.00	0.318	-.0001335	.0004105
bf30	.0005239	.0005317	0.99	0.324	-.0005182	.0015661
bf40	.0218384	.248862	0.09	0.930	-.4659222	.509599
deaw1	-1.453389	1.021447	-1.42	0.155	-3.455388	.5486112
dvcew1	0	(omitted)				
sepaw1	0	(omitted)				
accdw1	-.0050761	1.624722	-0.00	0.998	-3.189472	3.17932
movew1	-.0513738	1.125065	-0.05	0.964	-2.256461	2.153713
illw1	-.5020103	.7607393	-0.66	0.509	-1.993032	.9890113
shfamw1	.0137784	.0108362	1.27	0.204	-.0074601	.0350169

shhlw1	.0112349	.0171506	0.66	0.512	-.0223798	.0448495
shjobw1	-.0014008	.0136329	-0.10	0.918	-.0281207	.0253192
shrelaw1	-.0197593	.0117959	-1.68	0.094	-.0428787	.0033602
suprtw1	.0328165	.033418	0.98	0.326	-.0326817	.0983146
suchrw1	.0158253	.0298163	0.53	0.596	-.0426135	.0742642
havmilsq	-.000019	.0000262	-0.72	0.469	-.0000704	.0000324
radhlw1	0	(omitted)				
_cons	-89.90699	.	.	.	.	.

Note: 29 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	19	7	26
-	16	242	258
Total	35	249	284

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	54.29%
Specificity	$\Pr(- \sim D)$	97.19%
Positive predictive value	$\Pr(D +)$	73.08%
Negative predictive value	$\Pr(\sim D -)$	93.80%
False + rate for true ~D	$\Pr(+ \sim D)$	2.81%
False - rate for true D	$\Pr(- D)$	45.71%
False + rate for classified +	$\Pr(\sim D +)$	26.92%
False - rate for classified -	$\Pr(D -)$	6.20%
Correctly classified		91.90%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	284
number of covariate patterns =	284
Pearson $\chi^2(242)$ =	148.05
Prob > χ^2 =	1.0000

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

chunk 8 H1 test:Gender= 2 model Wave = 1 for HP2inthob

Model for gender==2 and wave == 1

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Logistic regression

Number of obs = 347

LR chi2(50) = 136.35

Prob > chi2 = 0.0000

Pseudo R2 = 0.4038

Log likelihood = -100.6444

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1576323	.0314369	5.01	0.000	.0960172	.2192474
_Ieduc_2	-13.15998	1390.096	-0.01	0.992	-2737.698	2711.378
_Ieduc_3	-12.34293	1390.096	-0.01	0.993	-2736.881	2712.195
_Ieduc_4	-11.76283	1390.096	-0.01	0.993	-2736.302	2712.776
_Ieduc_5	-12.38126	1390.096	-0.01	0.993	-2736.92	2712.157
_Ieduc_6	-12.87444	1390.096	-0.01	0.993	-2737.413	2711.664
_Ieduc_7	-11.28064	1390.098	-0.01	0.994	-2735.823	2713.262
_Ieduc_8	0	(omitted)				
occ1w1	-2.007966	2.670409	-0.75	0.452	-7.241872	3.225941
occ2w1	-1.42005	2.705	-0.52	0.600	-6.721752	3.881652
occ3w1	-2.637816	2.721093	-0.97	0.332	-7.971061	2.695429
occ4w1	-1.022244	2.749637	-0.37	0.710	-6.411434	4.366946
occ5w1	-2.685007	2.926173	-0.92	0.359	-8.4202	3.050187
occ6w1	-1.851042	2.900638	-0.64	0.523	-7.536188	3.834105
occ7w1	-.7751235	2.748828	-0.28	0.778	-6.162727	4.61248
occ8w1	1.738342	2.770527	0.63	0.530	-3.691792	7.168476
marrw11	-1.712685	1.961435	-0.87	0.383	-5.557026	2.131656
marrw12	-.7978205	2.432804	-0.33	0.743	-5.566028	3.970387
marrw13	-2.20107	1.785855	-1.23	0.218	-5.701282	1.299141
marrw15	-2.131202	2.204296	-0.97	0.334	-6.451543	2.189139
marrw16	-2.419024	2.291199	-1.06	0.291	-6.909692	2.071645
inc1w1	.4393464	2.638625	0.17	0.868	-4.732264	5.610957
inc2w1	1.095503	2.586215	0.42	0.672	-3.973385	6.16439
inc3w1	1.162288	2.607351	0.45	0.656	-3.948028	6.272603
inc4w1	2.352437	2.762052	0.85	0.394	-3.061086	7.765959
radhlw1	.016256	.0073318	2.22	0.027	.001886	.030626
havmil	.0027093	.0039697	0.68	0.495	-.0050712	.0104899
avgcumdosew1	.4525599	.2626453	1.72	0.085	-.0622155	.9673353
bf1	-.0392934	.0467729	-0.84	0.401	-.1309666	.0523799
bf4	-.1618817	.055024	-2.94	0.003	-.2697268	-.0540365
bf9	-.0557262	.0332131	-1.68	0.093	-.1208228	.0093703
bf10	.0039258	.0156035	0.25	0.801	-.0266565	.0345082
bf11	.0160165	.0531713	0.30	0.763	-.0881973	.1202303
bf14	-.00005	.0000899	-0.56	0.578	-.0002263	.0001262
bf15m	0	(omitted)				
bf20	.0307621	.0426341	0.72	0.471	-.0527993	.1143235
bf22	.0000428	.0000948	0.45	0.651	-.000143	.0002287
bf30	.0009017	.0003472	2.60	0.009	.0002212	.0015823
bf40	-.134405	.1339765	-1.00	0.316	-.396994	.1281841
deaw1	.0546666	.2268628	0.24	0.810	-.3899763	.4993096
dvcew1	1.590367	2.621038	0.61	0.544	-3.546772	6.727507

sepaw1	-1.421464	2.957733	-0.48	0.631	-7.218515	4.375587
accdw1	-.187097	1.01096	-0.19	0.853	-2.168543	1.794349
movew1	.280486	.7016446	0.40	0.689	-1.094712	1.655684
illw1	.0230342	.4319012	0.05	0.957	-.8234766	.8695451
shfamw1	.0000591	.0083223	0.01	0.994	-.0162524	.0163705
shhlw1	-.0037244	.0125633	-0.30	0.767	-.0283479	.0208992
shjobw1	-.0032054	.0093218	-0.34	0.731	-.0214757	.0150649
shrelaw1	-.0051493	.0079574	-0.65	0.518	-.0207454	.0104468
suprtw1	.0012475	.0121595	0.10	0.918	-.0225847	.0250796
suchrw1	-.0019168	.0162004	-0.12	0.906	-.0336689	.0298353
havmilsq	-1.74e-06	5.49e-06	-0.32	0.752	-.0000125	9.02e-06
radhlw1	0	(omitted)				
_cons	3.925606	1390.1	0.00	0.998	-2720.621	2728.472

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	37	7	44
-	29	274	303
Total	66	281	347

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	56.06%
Specificity	$\Pr(- \sim D)$	97.51%
Positive predictive value	$\Pr(D +)$	84.09%
Negative predictive value	$\Pr(\sim D -)$	90.43%
False + rate for true ~D	$\Pr(+ \sim D)$	2.49%
False - rate for true D	$\Pr(- D)$	43.94%
False + rate for classified +	$\Pr(\sim D +)$	15.91%
False - rate for classified -	$\Pr(D -)$	9.57%
Correctly classified		89.63%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	347
number of covariate patterns =	347
Pearson chi2(296) =	450.83
Prob > chi2 =	0.0000

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

Log-Lik Intercept Only:	-168.821	Log-Lik Full Model:	-100.644
D(293):	201.289	LR(50):	136.353
		Prob > LR:	0.000
McFadden's R2:	0.404	McFadden's Adj R2:	0.084
Maximum Likelihood R2:	0.325	Cragg & Uhler's R2:	0.522
McKelvey and Zavoina's R2:	0.648	Efron's R2:	0.466
Variance of y*:	9.347	Variance of error:	3.290
Count R2:	0.896	Adj Count R2:	0.455
AIC:	0.891	AIC*n:	309.289
BIC:	-1512.563	BIC':	156.113

```

1120 .
1121 . label var radhlw1 "Self-perceived Chornobyl health threat in wave 1"

1122 .
1123 . 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

```

```

1124 .
1125 .
1126 . forvalues j=1/1 {
    2. set more off
    3.
1127 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
    > bf4 bf14 bf40
    4.
1128 . foreach var in HP2inthob {
    5. local wlbfs bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40
    6. di _skip(2)
    7. di as input "Full main model for `var' for wave= `j' "
    8. di _skip(4)
    9. di as input "chunk 8 H1 test:Gender= male model Wave = `j' for `e(depvar)'"
    > ar)' "
    10. di _skip(4)
    11. title "Full Nottingham Part 2 subscale models " "males on wave=`j'"
    12. des bf5m shfamw1 radhlw1 bf4m
    13. xi: logistic `var' age radhlw1 bf4 bf10 bf40 shrelaw1 ///
    > suchrw1 if gender==1, coef diffcult 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
marrw1	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inc1w1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf14	float	%9.0g		bf14= max(0, radw2 - 10) * bf12
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2inthob for wave= 1

chunk 8 H1 test:Gender= male model Wave = 1 for HP2inthob

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0200969	.0187425	1.07	0.284	-.0166377	.0568315
radhlw1	.0186628	.006222	3.00	0.003	.0064679	.0308576
bf4	-.1419329	.0385628	-3.68	0.000	-.2175146	-.0663512
bf10	-.0002913	.0097452	-0.03	0.976	-.0193915	.0188088
bf40	.2956738	.1272383	2.32	0.020	.0462913	.5450564
shrelaw1	-.0046332	.0053472	-0.87	0.386	-.0151134	.005847
suchrw1	.0141811	.015058	0.94	0.346	-.015332	.0436942
_cons	-3.536445	1.260759	-2.81	0.005	-6.007486	-1.065403

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	13	4	17
-	25	298	323
Total	38	302	340

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	34.21%
Specificity	$\Pr(- \sim D)$	98.68%
Positive predictive value	$\Pr(D +)$	76.47%
Negative predictive value	$\Pr(\sim D -)$	92.26%

False + rate for true ~D	$\Pr(+ \sim D)$	1.32%
False - rate for true D	$\Pr(- D)$	65.79%
False + rate for classified +	$\Pr(\sim D +)$	23.53%
False - rate for classified -	$\Pr(D -)$	7.74%

Correctly classified	91.47%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    332
Pearson chi2(324) =      299.10
Prob > chi2 =      0.8360

```

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

Log-Lik Intercept Only:	-119.064	Log-Lik Full Model:	-86.807
D(332):	173.613	LR(7):	64.515
		Prob > LR:	0.000
McFadden's R2:	0.271	McFadden's Adj R2:	0.204
Maximum Likelihood R2:	0.173	Cragg & Uhler's R2:	0.343
McKelvey and Zavoina's R2:	0.425	Efron's R2:	0.237
Variance of y*:	5.726	Variance of error:	3.290
Count R2:	0.915	Adj Count R2:	0.237
AIC:	0.558	AIC*n:	189.613
BIC:	-1761.596	BIC':	-23.712

Note: bf4m is necessary for bf5 but if bf4m is in model bf5 is not signif.
Therefore, bf5 is not deemed significant.

```

1129 .
1130 . cap gen bf4Xd1 = bf4*avgcumdosew1

1131 . cap gen bf10Xd1= bf10*avgcumdosew1

1132 . cap gen bf40Xd1 = bf40*agecumdosew1

1133 .
1134 . scalar SigdoseMEinthob = "no"

1135 . scalar MainEffMw1 = "radhlw1 bf4 bf40"

1136 .
1137 . title3 "wave 1 Main effects Dose=> Interests and Hobbies impact identificati
> on"

```

```

title3 : wave 1 Main effects Dose=> Interests and Hobbies impact identificatio
> n
18 Jun 2012
18:17:42
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/hltests
> /hlpt2
Data file chwide16june2012.dta currently has 2380 variables and 703 obs
> ervations

```

```

1138 . forvalues j=1/1 {
      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 wlbfs bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40
      6. di as input "Full main model for `var' for wave= `j' "
      7. di _skip(4)
      8. di as input "chunk 8 H1 test:Gender= male  model Wave = `j' for `e(dep
      > ar)'"
      9. di _skip(4)
      10.
1141 .
1142 .      xi: logistic `var' age ///
      >          radhlw`j' avgcumdosew`j' ///
      >          shfamw`j' bf4 ///
      >          bf40 bf4Xd1 bf40Xd1 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
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inclw1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986

```

inc2w1          double %15.0g      LABJ      Income is just sufficient for
                                                basic neccessities in 1986
inc3w1          double %15.0g      LABJ      Income is sufficient for basics
                                                plus extra purchases/savings
                                                in 1986
inc4w1          double %15.0g      LABJ      Income allows to comfortably
                                                afford luxury items in 1986
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= 1

chunk 8 H1 test:Gender= male model Wave = 1 for HP2inthob

Logistic regression	Number of obs	=	339
	LR chi2(8)	=	69.68
	Prob > chi2	=	0.0000
Log likelihood = -84.103355	Pseudo R2	=	0.2929

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0229294	.0193857	1.18	0.237	-.015066	.0609247
radhlw1	.0203775	.0063075	3.23	0.001	.008015	.03274
avgcumdosew1	6.417441	3.545095	1.81	0.070	-.530818	13.3657
shfamw1	.0031998	.0052579	0.61	0.543	-.0071055	.013505
bf4	.0015257	.0840489	0.02	0.986	-.163207	.1662585
bf40	.4371492	.1715289	2.55	0.011	.1009587	.7733397
bf4Xd1	-.469083	.2679615	-1.75	0.080	-.9942779	.0561118
bf40Xd1	-.724812	.4037974	-1.79	0.073	-1.51624	.0666164
_cons	-5.810547	1.708506	-3.40	0.001	-9.159156	-2.461938

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	11	6	17
-	27	295	322
Total	38	301	339

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	28.95%
Specificity	$\Pr(- \sim D)$	98.01%
Positive predictive value	$\Pr(D +)$	64.71%
Negative predictive value	$\Pr(\sim D -)$	91.61%
False + rate for true ~D	$\Pr(+ \sim D)$	1.99%
False - rate for true D	$\Pr(- D)$	71.05%
False + rate for classified +	$\Pr(\sim D +)$	35.29%
False - rate for classified -	$\Pr(D -)$	8.39%
Correctly classified		90.27%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      339
number of covariate patterns =    337
Pearson chi2(328) =      260.58
Prob > chi2 =      0.9975

```

Measures of Fit for logistic of HP2inthob

Log-Lik Intercept Only:	-118.946	Log-Lik Full Model:	-84.103
D(330):	168.207	LR(8):	69.684
		Prob > LR:	0.000
McFadden's R2:	0.293	McFadden's Adj R2:	0.217
Maximum Likelihood R2:	0.186	Cragg & Uhler's R2:	0.368
McKelvey and Zavoina's R2:	0.640	Efron's R2:	0.242
Variance of y*:	9.132	Variance of error:	3.290
Count R2:	0.903	Adj Count R2:	0.132
AIC:	0.549	AIC*n:	186.207
BIC:	-1754.373	BIC':	-23.076

```

1143 . scalar SigDoseInthbMw1 = "no"

1144 . scalar MainEffInthbMw1 = "age radhlw1 shfamw1"

1145 . scalar InthbModMw1 = "none"

1146 .
1147 . *-----chunk 8   female moderator models
1148 . title4 "trimmed Moderators of female Dose => Interests and Hobbies Impact"

```

```

trimmed Moderators of female Dose => Interests and Hobbies Impact

```

```

1149 .
1150 .
1151 . forvalues j=1/1 {
      2. set more off
      3.
1152 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      >   bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1153 . foreach var in HP2inthob {
      5. local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40
      6.   di as input "Full main model for `var' for wave= `j' "
      7.   di _skip(4)
      8.   di as input  "chunk 8 H1 test:Gender= male   model Wave = `j' for `e(depvar)'"
      > ar)' "
      9.   di _skip(4)
     10.   title "Full Nottingham Part 2 subscale models for females "
     11.
1154 .       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
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inc1w1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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= 1

chunk 8 H1 test:Gender= male model Wave = 1 for HP2inthob

Logistic regression	Number of obs	=	362
	LR chi2(4)	=	91.22
	Prob > chi2	=	0.0000
Log likelihood = -126.30289	Pseudo R2	=	0.2653

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0702541	.0161129	4.36	0.000	.0386734	.1018347
radhlwl	.0195656	.004896	4.00	0.000	.0099695	.0291616
avgcumdosewl	.2200581	.222466	0.99	0.323	-.2159672	.6560835
bf4	-.1103614	.0315756	-3.50	0.000	-.1722484	-.0484743
_cons	-5.707394	1.074147	-5.31	0.000	-7.812684	-3.602104

Classified	True		Total
	D	~D	
+	29	10	39
-	37	286	323
Total	66	296	362

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

Sensitivity	$\Pr(+ D)$	43.94%
Specificity	$\Pr(- \sim D)$	96.62%
Positive predictive value	$\Pr(D +)$	74.36%
Negative predictive value	$\Pr(\sim D -)$	88.54%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	3.38%
False - rate for true D	$\Pr(- D)$	56.06%
False + rate for classified +	$\Pr(\sim D +)$	25.64%
False - rate for classified -	$\Pr(D -)$	11.46%
Correctly classified		87.02%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	362
number of covariate patterns =	360
Pearson $\chi^2(355)$ =	441.04
Prob > χ^2 =	0.0012

Measures of Fit for logistic of HP2inthob

Log-Lik Intercept Only:	-171.912	Log-Lik Full Model:	-126.303
D(357):	252.606	LR(4):	91.217
		Prob > LR:	0.000
McFadden's R2:	0.265	McFadden's Adj R2:	0.236
Maximum Likelihood R2:	0.223	Cragg & Uhler's R2:	0.363
McKelvey and Zavoina's R2:	0.426	Efron's R2:	0.309
Variance of y*:	5.731	Variance of error:	3.290
Count R2:	0.870	Adj Count R2:	0.288
AIC:	0.725	AIC*n:	262.606
BIC:	-1850.711	BIC':	-67.651

```

1155 . scalar SigdoseInthbFw1 = "no"

1156 . scalar MainEffInthbFw1 = "age radhlw1 bf4"

1157 .
1158 . title4 "*-----chunk 8 testing female interests and hobbies moderators"

```

```

*-----chunk 8 testing female interests and hobbies moderators

```

```

1159 .
1160 .
1161 . forvalues j=1/1 {
      2. set more off
      3.
1162 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      >   bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1163 . cap gen ageXd1 = age*avgcumdosew1
      5. foreach var in HP2inthob {
      6. local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40
      7. di _skip(4)
      8. di as input "Full main model for `var' for wave= `j' "
      9. di _skip(4)
     10. di as input  "chunk 8 H1 test:Gender= male  model Wave = `j' for `e(dep
      > ar)' "
     11. di _skip(4)
     12.
1164 .      xi: logistic `var' age    ///
      >          radhlw`j' avgcumdosew`j' ///
      >          bf4  bf4Xd1 ageXd1 radhlw1Xd1 ///
      >          if gender==2, coef  difficult iterate(50)
     13.          estat class
     14.          estat gof
     15.          fitstat
     16. }
     17. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw11	byte	%8.0g		marrw1==1. single
marrw12	byte	%8.0g		marrw1==2. cohabitating
marrw13	byte	%8.0g		marrw1==3. married
marrw14	byte	%8.0g		marrw1==4. separated
marrw15	byte	%8.0g		marrw1==5. divorced
marrw16	byte	%8.0g		marrw1==6. widowed
inc1w1	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1986
inc2w1	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1986
inc3w1	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1986
inc4w1	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1986
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= 1

chunk 8 H1 test:Gender= male model Wave = 1 for HP2inthob

Logistic regression

Number of obs = 362

LR chi2(7) = 91.60

Prob > chi2 = 0.0000

Log likelihood = -126.114

Pseudo R2 = 0.2664

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.067857	.0189391	3.58	0.000	.030737	.1049771
radhlw1	.0207366	.0056517	3.67	0.000	.0096595	.0318137
avgcumdosew1	-.1191818	2.032868	-0.06	0.953	-4.103531	3.865167
bf4	-.1190418	.0397853	-2.99	0.003	-.1970196	-.0410639
bf4Xd1	.0200494	.0609254	0.33	0.742	-.0993622	.139461
ageXd1	.0057703	.0330253	0.17	0.861	-.0589581	.0704986
radhlw1Xd1	-.001995	.0056092	-0.36	0.722	-.0129888	.0089987
_cons	-5.587746	1.23496	-4.52	0.000	-8.008224	-3.167268

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	30	11	41
-	36	285	321
Total	66	296	362

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	45.45%
Specificity	$\Pr(- \sim D)$	96.28%
Positive predictive value	$\Pr(D +)$	73.17%
Negative predictive value	$\Pr(\sim D -)$	88.79%

False + rate for true ~D	$\Pr(+ \sim D)$	3.72%
False - rate for true D	$\Pr(- D)$	54.55%
False + rate for classified +	$\Pr(\sim D +)$	26.83%
False - rate for classified -	$\Pr(D -)$	11.21%

Correctly classified	87.02%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

```

        number of observations =      362
number of covariate patterns =      360
        Pearson chi2(352) =     446.24
        Prob > chi2 =           0.0005

```

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

Log-Lik Intercept Only:	-171.912	Log-Lik Full Model:	-126.114
D(354):	252.228	LR(7):	91.595
		Prob > LR:	0.000
McFadden's R2:	0.266	McFadden's Adj R2:	0.220
Maximum Likelihood R2:	0.224	Cragg & Uhler's R2:	0.365
McKelvey and Zavoina's R2:	0.431	Efron's R2:	0.311
Variance of y*:	5.782	Variance of error:	3.290
Count R2:	0.870	Adj Count R2:	0.288
AIC:	0.741	AIC*n:	268.228
BIC:	-1833.414	BIC':	-50.354

```
1165 . scalar InthbModFw1 = "none"
```

```
1166 .
```

```
1167 . title4 " dose-  interests and hobbies  mediator effect models"
```

```
    dose-  interests and hobbies  mediator effect models
```

```
1168 .
```

```
1169 . * age is a mediating effect for males for Dose=> sex life for men
```

```
1170 .
```

```
1171 . glm age avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood =  -1331.608
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	148.5632
Deviance	= 50214.37624	(1/df) Deviance	=	148.5632
Pearson	= 50214.37624	(1/df) Pearson	=	148.5632
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]
		<u>AIC</u>	=	7.844753
Log likelihood	= -1331.607976	<u>BIC</u>	=	48244.19

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
1172 . 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.)

```
1173 .
```

```
1174 .
1175 . des illw1
```

variable name	storage type	display format	value label	variable label
illw1	double	%8.0g		Total number of illnesses experienced in time period 1976-1986

```
1176 . glm illw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-151.48261**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
Deviance	= 48.52808533	Scale parameter	=	.1435742
Pearson	= 48.52808533	(1/df) Deviance	=	.1435742
		(1/df) Pearson	=	.1435742
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	.9028389
Log likelihood	= -151.4826069	<u>BIC</u>	=	-1921.656

illw1	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew1	.0087277	.0123318		0.71	0.479	-.0154423	.0328976
_cons	.0962541	.0212201		4.54	0.000	.0546635	.1378446

```
1177 . glm HP2inthob illw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

Iteration 1: deviance = **237.5512**
 Iteration 2: deviance = **236.4934**
 Iteration 3: deviance = **236.4907**
 Iteration 4: deviance = **236.4907**

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 236.4906909	(1/df) Deviance	=	.6996766
Pearson	= 341.1245148	(1/df) Pearson	=	1.009244

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1733.693

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw1	.2627617	.1703489	1.54	0.123	-.071116	.5966393
_cons	-1.249391	.0787713	-15.86	0.000	-1.40378	-1.095002

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

1178 .
 1179 . * radhlw1 is a possible mediator for wave 1 males and interests and hobbies.
 1180 . des radhlw1

variable name	storage type	display format	value label	variable label
radhlw1	double	%8.0g		Self-perceived Chornobyl health threat in wave 1

1181 . glm radhlw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1710.3417

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1378.645
Deviance = 465981.8893	(1/df) Deviance	=	1378.645
Pearson = 465981.8893	(1/df) Pearson	=	1378.645

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

	AIC	=	10.0726
Log likelihood = -1710.341694	BIC	=	464011.7

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	2.398285	1.208412	1.98	0.047	.0298407	4.766729
_cons	44.66477	2.079384	21.48	0.000	40.58925	48.74029

```
1182 . glm HP2inthob radhlw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 212.8979
Iteration 2:  deviance = 203.1654
Iteration 3:  deviance = 202.4404
Iteration 4:  deviance = 202.4342
Iteration 5:  deviance = 202.4342
Iteration 6:  deviance = 202.4342
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  MQL Fisher scoring                  Residual df     =       338
                   (IRLS EIM)                           Scale parameter =        1
Deviance          = 202.4342472                         (1/df) Deviance =  .5989179
Pearson           = 366.2964245                         (1/df) Pearson  =  1.083717
```

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

```
BIC = -1767.749
```

HP2inthob	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
radhlw1	.0153039	.0021709	7.05	0.000	.0110489	.0195589
_cons	-2.114122	.1635196	-12.93	0.000	-2.434615	-1.79363

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

```
1183 .
1184 .
1185 . des shfamw1
```

variable name	storage type	display format	value label	variable label
shfamw1	double	%8.0g		Percentage of strains and hassles related to family in 1986

```
1186 . glm shfamw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1722.3986
```

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1524.9
Deviance = 513891.1861	(1/df) Deviance	=	1524.9
Pearson = 513891.1861	(1/df) Pearson	=	1524.9

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

	<u>AIC</u>	=	10.17344
Log likelihood = -1722.398621	<u>BIC</u>	=	511927.8

shfamw1	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew1	-.8322929	1.270907	-0.65	0.513	-3.323226	1.65864	
_cons	38.72924	2.190054	17.68	0.000	34.43681	43.02167	

```
1187 . glm HP2inthob shfamw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 236.3247
Iteration 2: deviance = 234.8343
Iteration 3: deviance = 234.8258
Iteration 4: deviance = 234.8258
Iteration 5: deviance = 234.8258
```

Generalized linear models	No. of obs	=	339
Optimization : ML Fisher scoring	Residual df	=	337
(IRLS EIM)	Scale parameter	=	1
Deviance = 234.8258277	(1/df) Deviance	=	.6968125
Pearson = 340.806701	(1/df) Pearson	=	1.011296

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

	BIC	=	-1728.536
--	-----	---	-----------

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw1	.0039265	.0018944	2.07	0.038	.0002136	.0076394
_cons	-1.380389	.1125461	-12.27	0.000	-1.600976	-1.159803

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

```
1188 .
1189 . des bf5m
```

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

```
1190 . glm bf5m avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-2272.9908**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	37743.06
Deviance = 12757154.41	(1/df) Deviance	=	37743.06
Pearson = 12757154.41	(1/df) Pearson	=	37743.06

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

	<u>AIC</u>	=	13.3823
Log likelihood = -2272.990823	<u>BIC</u>	=	1.28e+07

bf5m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	14.60088	6.32277	2.31	0.021	2.208475	26.99328
_cons	107.248	10.87995	9.86	0.000	85.92368	128.5723

```
1191 . 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.)

```
1192 .
```

```
1193 . glm bf4 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1026.9659
```

```
Generalized linear models                               No. of obs      =       340
Optimization      : ML                                 Residual df     =       338
Scale parameter = 24.75428
Deviance          = 8366.946191                        (1/df) Deviance = 24.75428
Pearson           = 8366.946191                        (1/df) Pearson  = 24.75428
```

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

```
Log likelihood    = -1026.965868                      AIC           = 6.05274
                                                           BIC           = 6396.763
```

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.1031788	.161925	-0.64	0.524	-.4205461	.2141884
_cons	12.54134	.2786337	45.01	0.000	11.99523	13.08746

```
1194 . 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      :  MQL 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.)

```

1195 .
1196 .
1197 . scalar inthobMw1 = "age "

1198 .
1199 . * age is a mediating effect for females for Dose=> sex life for women
1200 . glm age avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.325**

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
		Scale parameter	=	136.455
Deviance	= 49260.25928	(1/df) Deviance	=	136.455
Pearson	= 49260.25928	(1/df) Pearson	=	136.455

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

	<u>AIC</u>	=	7.759366
Log likelihood = -1406.325011	<u>BIC</u>	=	47132.38

	OIM					
age	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```

1201 . 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.)

```
1202 .
1203 . * illw1 is a mediating effect for females for Dose=> sex life for women
1204 . glm illw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-259.70777**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.2462383
Deviance = 88.89203958	(1/df) Deviance	=	.2462383
Pearson = 88.89203958	(1/df) Pearson	=	.2462383

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

	<u>AIC</u>	=	1.441916
Log likelihood = -259.7077741	<u>BIC</u>	=	-2038.987

illw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.0655142	.0474789	1.38	0.168	-.0275426	.1585711
_cons	.1570822	.0305304	5.15	0.000	.0972436	.2169207

```
1205 . glm HP2inthob illw1 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 344.2026
Iteration 2: deviance = 344.1217
Iteration 3: deviance = 344.1216
Iteration 4: deviance = 344.1216
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 344.121648	(1/df) Deviance	=	.9532456
Pearson = 362.9817892	(1/df) Pearson	=	1.00549

[Bernoulli]
[Probit]

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illwl	.04902	.1470127	0.33	0.739	-.2391195	.3371596
_cons	-.9175059	.0797583	-11.50	0.000	-1.073829	-.7611824

```
1206 .
1207 . des bf4    // soma recentered
```

```
1208 . * bf4 is a mediating effect for females for Dose=> sex life for women
1209 . glm bf4 avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

Generalized linear models
Optimization : ML

No. of obs	=	363
Residual df	=	361
Scale parameter	=	26.52082
(1/df) Deviance	=	26.52082
(1/df) Pearson	=	26.52082

[Gaussian]
[Identity]

AIC = 6.121302
BIC = 7446.136

	OIM					
bf4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-1.508835	.4927379	-3.06	0.002	-2.474583	-.5430862
_cons	10.99384	.3168463	34.70	0.000	10.37284	11.61485

```
1210 . 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		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.0993749	.0142594	-6.97	0.000	-.1273229	-.071427
_cons	.0117358	.1447759	0.08	0.935	-.2720197	.2954914

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

```
1211 .
1212 . des bf4m // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1213 . * bf4m is a possible mediating effect for female sex life
```

```
1214 . glm bf4m avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1140.521
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	31.548
Deviance = 11388.82943	(1/df) Deviance	=	31.548
Pearson = 11388.82943	(1/df) Pearson	=	31.548

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

	<u>AIC</u>	=	6.294882
Log likelihood = -1140.521046	<u>BIC</u>	=	9260.95

bf4m	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew1	-1.563541	.5374133	-2.91	0.004	-2.616852	-.5102303	
_cons	18.82212	.3455741	54.47	0.000	18.1448	19.49943	

```
1215 . 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.)

```
1216 .
1217 . des shfamw1
```

variable name	storage type	display format	value label	variable label
shfamw1	double	%8.0g		Percentage of strains and hassles related to family in 1986

```
1218 . glm shfamw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1722.3986**

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1524.9
Deviance = 513891.1861	(1/df) Deviance	=	1524.9
Pearson = 513891.1861	(1/df) Pearson	=	1524.9

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

	<u>AIC</u>	=	10.17344
Log likelihood = -1722.398621	<u>BIC</u>	=	511927.8

shfamw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.8322929	1.270907	-0.65	0.513	-3.323226	1.65864
_cons	38.72924	2.190054	17.68	0.000	34.43681	43.02167

```
1219 . glm HP2sxlife shfamw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =   339.011
Iteration 2:  deviance =   338.8015
Iteration 3:  deviance =   338.8014
Iteration 4:  deviance =   338.8014
```

```
Generalized linear models                               No. of obs      =       339
Optimization      :  MQL Fisher scoring                 Residual df     =       337
                   (IRLS EIM)                          Scale parameter =         1
Deviance          =   338.8013645                       (1/df) Deviance =   1.005345
Pearson           =   339.2776273                       (1/df) Pearson  =   1.006759
```

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

```
BIC = -1624.561
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw1	.0019797	.0019787	1.00	0.317	-.0018986	.0058579
_cons	-.9179132	.1113818	-8.24	0.000	-1.136218	-.6996088

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

```
1220 .
1221 . des shrelaw1
```

variable name	storage type	display format	value label	variable label
shrelaw1	double	%8.0g		Percentage of strains and hassles related to relationships in 1986

```
1222 . glm shrelaw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1715.4166
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1420.421
Deviance = 480102.3567	(1/df) Deviance	=	1420.421
Pearson = 480102.3567	(1/df) Pearson	=	1420.421

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

	<u>AIC</u>	=	10.10245
Log likelihood = -1715.416629	<u>BIC</u>	=	478132.2

shrelaw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	-.0649405	1.226584	-0.05	0.958	-2.469002	2.339121
_cons	29.57199	2.110654	14.01	0.000	25.43518	33.7088

```
1223 . glm HP2inthob shrelaw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 238.2169
Iteration 2: deviance = 237.1515
Iteration 3: deviance = 237.1479
Iteration 4: deviance = 237.1479
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 237.1479061	(1/df) Deviance	=	.701621
Pearson = 340.4217715	(1/df) Pearson	=	1.007165

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

	BIC	=	-1733.036
--	-----	---	-----------

HP2inthob	EIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
shrelaw1	.0022898	.0019458	1.18	0.239		-.0015239	.0061035
_cons	-1.289369	.0985609	-13.08	0.000		-1.482545	-1.096193

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

```
1224 .
1225 . title4 "6. Summary matrix for dose - interests and hobbies impact"
```

```
6. Summary matrix for dose - interests and hobbies impact
```

```
1226 . *xx summary of mediating effects: males only age and illw1 2
1227 . *xx          females: age
1228 . scalar SigDoseInthbMw1 = "no"

1229 . scalar MainEffInthbMw1 = "age radhlw1 shfamw1"

1230 . scalar InthbModMw1 = "none"

1231 . scalar InthbModFw1 = "none"

1232 . scalar SigdoseInthbFw1 = "no"

1233 . scalar MainEffInthbFw1 = "age radhlw1 bf4"

1234 . * summary of inthob moderator effects none
1235 . scalar inthobMedMw1 = "age "

1236 . scalar inthobMedFw1 = "age bf4 illw1 bf4m"

1237 . scalar SigdoseMEinthob = "no"

1238 . scalar MainEffMw1 = "radhlw1 bf4 bf40"
```

```

1239 . * no sign main dose effect for males
1240 . * no male moderators
1241 . * 3 signif main effects in male main effect model
1242 .
1243 .
1244 . * no signif dose main effect for females
1245 . * 3 main female effects
1246 . * no significant female moderators
1247 . di _skip(4)

1248 . matrix define inthbMw1 = J(1,8, 0)

1249 . matrix define inthbFw1 = J(1,8, 0)

1250 . matrix colnames inthbMw1= hypnum ptnum wave gender medsig numMASig numMods
    > ig numMed

1251 . matrix colnames inthbFw1= hypnum ptnum wave gender medsig numMASig numMods
    > ig numMed

1252 . matrix define inthbMw1= (1, 2, 1, 1, 0, 3, 0, 1 )

1253 . matrix define inthbFw1= (1, 2, 1, 2, 0, 3, 0, 4 )

1254 . matrix rowname inthbMw1 = inthbM

1255 . matrix rowname inthbFw1 = inthobF

1256 . matlist inthbMw1

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	inthbM	1	2	1	1	0	
> 3	0	1					

```
1257 .          matlist  inthbFw1
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	inthobF	1	2	1	2	0	
> 3	0	4					

```
1258 .          matrix define H1pt2w1 = ( wkMw1 \ wkFw1 \ hmcrMw1 \ hmcrFw1 \ s
> pMw1 ///
>          \ spFw1 \ prbfamMw1 \ prbfamFw1 \ sxlifeMw1 \ sxlifeFw1 \ inth
> bMw1 \ inthbFw1)
```

```
1259 .
```

```
1260 .          matlist H1pt2w1
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 1	1	2					
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 2	0	2					
	spMw1	1	2	1	1	1	
> 2	2	1					
	spFw1	1	2	1	2	0	
> 5	0	2					
	prbfamMw1	1	2	1	1	0	
> 2	0	0					
	prbfamFw1	1	2	1	2	0	
> 3	0	2					
	sxlifeMw1	1	2	1	1	0	
> 3	0	1					
	sxlifeFw1	1	2	1	2	0	
> 4	0	5					
	inthbM	1	2	1	1	0	
> 3	0	1					
	inthobF	1	2	1	2	0	
> 3	0	4					

```
1261 .      matrix colnames H1pt2w1 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
1262 .      matrix rownames H1pt2w1 =    wkMw1 wkFw1 hmcrMw1 hmcrFw1 socprbMw1
> socprbFw1 prbfamMw1 prbFamFw1 sxlifeMw1 sxlifeFw1 inthbMw1 inthbFw1
```

```
1263 .      matlist H1pt2w1
```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2	0	1					
	wkFw1	1	2	1	2	0	
> 1	1	2					
	hmcrMw1	1	2	1	1	0	
> 2	0	1					
	hmcrFw1	1	2	1	2	0	
> 2	0	2					
	socprbMw1	1	2	1	1	1	
> 2	2	1					
	socprbFw1	1	2	1	2	0	
> 5	0	2					
	prbfamMw1	1	2	1	1	0	
> 2	0	0					
	prbFamFw1	1	2	1	2	0	
> 3	0	2					
	sxlifeMw1	1	2	1	1	0	
> 3	0	1					
	sxlifeFw1	1	2	1	2	0	
> 4	0	5					
	inthbMw1	1	2	1	1	0	
> 3	0	1					
	inthbFw1	1	2	1	2	0	
> 3	0	4					

Male model wave 1 dose-hp2vactn moderator model

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: occ6w1 != 0 predicts failure perfectly
 occ6w1 dropped and 4 obs not used

note: occ7w1 != 0 predicts failure perfectly
 occ7w1 dropped and 4 obs not used

note: marrw15 != 0 predicts success perfectly
 marrw15 dropped and 1 obs not used

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

note: dvcew1 != 0 predicts failure perfectly
 dvcew1 dropped and 2 obs not used

note: sepaw1 != 0 predicts success perfectly
 sepaw1 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity

note: marrw16 omitted because of collinearity

note: radhlw1 omitted because of collinearity

note: avgcumdosew1 omitted because of collinearity

Logistic regression	Number of obs	=	284
	LR chi2(41)	=	101.69
	Prob > chi2	=	0.0000
Log likelihood = -57.124451	Pseudo R2	=	0.4709

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1177419	.0451828	2.61	0.009	.0291854	.2062985
_Ieduc_2	-3.055944	1.716937	-1.78	0.075	-6.421078	.3091893
_Ieduc_3	-.212761	.8269168	-0.26	0.797	-1.833488	1.407966
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.158373	.8405787	-0.19	0.851	-1.805877	1.489131
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w1	.9327826	3.048048	0.31	0.760	-5.041281	6.906846
occ2w1	1.600773	3.127281	0.51	0.609	-4.528585	7.730132
occ3w1	.8629517	3.222587	0.27	0.789	-5.453202	7.179105
occ4w1	.7047753	3.193274	0.22	0.825	-5.553927	6.963477
occ5w1	.9185675	3.369728	0.27	0.785	-5.685978	7.523113
occ6w1	0	(omitted)				
occ7w1	0	(omitted)				
occ8w1	2.576584	3.31921	0.78	0.438	-3.928947	9.082116
marrw11	8.063251	1454.164	0.01	0.996	-2842.047	2858.173
marrw12	8.396586	1454.165	0.01	0.995	-2841.715	2858.509
marrw13	6.592655	1454.165	0.00	0.996	-2843.518	2856.703
marrw15	0	(omitted)				
marrw16	0	(omitted)				
inc1w1	1.72241	3.405241	0.51	0.613	-4.951739	8.396559
inc2w1	1.681005	3.353329	0.50	0.616	-4.891398	8.253409
inc3w1	1.742795	3.224514	0.54	0.589	-4.577137	8.062726
inc4w1	.22304	3.501992	0.06	0.949	-6.640738	7.086818
radhlw1	.0177143	.0102482	1.73	0.084	-.0023719	.0378004
havmil	-.000285	.0120623	-0.02	0.981	-.0239267	.0233567
avgcumdosew1	-.101335	.173417	-0.58	0.559	-.441226	.238556
bf1	-.067538	.109717	-0.62	0.538	-.2825793	.1475033
bf4	-.2732381	.0860278	-3.18	0.001	-.4418495	-.1046267
bf9	.045179	.0491094	0.92	0.358	-.0510737	.1414317
bf10	-.0859725	.0443879	-1.94	0.053	-.1729712	.0010262
bf11	.0439137	.1246785	0.35	0.725	-.2004517	.288279
bf14	-.0000515	.0001058	-0.49	0.627	-.0002589	.0001559
bf15m	0	(omitted)				
bf20	.0464251	.1033689	0.45	0.653	-.1561741	.2490244
bf22	.0001389	.0001358	1.02	0.306	-.0001273	.0004051
bf30	-.001371	.0006346	-2.16	0.031	-.0026148	-.0001273
bf40	.3396411	.2165949	1.57	0.117	-.0848772	.7641593
deaw1	-.5911018	.7169403	-0.82	0.410	-1.996279	.8140753
dvcew1	0	(omitted)				
sepaw1	0	(omitted)				
accdw1	1.690611	1.483962	1.14	0.255	-1.2179	4.599123
movew1	.7972512	.7853957	1.02	0.310	-.7420961	2.336598
illw1	-1.434715	.7967422	-1.80	0.072	-2.996301	.1268714
shfamw1	-.0116324	.0105102	-1.11	0.268	-.032232	.0089671

shhlw1	.0339732	.0188557	1.80	0.072	-.0029832	.0709297
shjobw1	.0121109	.0125268	0.97	0.334	-.0124412	.036663
shrelaw1	-.0146336	.0112271	-1.30	0.192	-.0366384	.0073711
suprtw1	.1086712	.0510741	2.13	0.033	.0085679	.2087746
suchrw1	-.0573692	.0444525	-1.29	0.197	-.1444944	.0297561
havmilsq	-6.00e-06	.0000223	-0.27	0.787	-.0000496	.0000376
radhlw1	0	(omitted)				
avgcumdosew1	0	(omitted)				
_cons	-21.03776	1454.176	-0.01	0.988	-2871.17	2829.095

Note: 1 failure and 0 successes completely determined.

```

title3 : trimmed hp2vactn main effects models for H1 no direct dose effect for
> male
18 Jun 2012
18:18:21
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/hltests
> /hlpt2
Data file chwide16june2012.dta currently has 2388 variables and 703 obs
> ervations

```

	hp2hmc~e	age	deaw1	shjobw1	bf7m	shjobw1	havmilsq
hp2hmcare	1.0000						
	340						
age	0.2761*	1.0000					
	0.0000						
	340	340					
deaw1	0.0095	0.2204*	1.0000				
	1.0000	0.0015					
	340	340	340				
shjobw1	0.2490*	0.2162*	-0.0439	1.0000			
	0.0001	0.0021	1.0000				
	340	340	340	340			
bf7m	-0.1339	-0.0182	0.1915*	-0.2097*	1.0000		
	0.3860	1.0000	0.0137	0.0035			
	340	340	340	340	340		
shjobw1	0.2490*	0.2162*	-0.0439	1.0000*	-0.2097*	1.0000	
	0.0001	0.0021	1.0000	0.0000	0.0035		
	340	340	340	340	340	340	

havmilsq	-0.0347 1.0000 340	0.0207 1.0000 340	-0.0393 1.0000 340	0.0027 1.0000 340	-0.0420 1.0000 340	0.0027 1.0000 340	1.0000 340
radhlw1	0.2183* 0.0018 340	0.3167* 0.0000 340	0.0077 1.0000 340	0.4115* 0.0000 340	0.0528 1.0000 340	0.4115* 0.0000 340	-0.1218 0.5939 340
avgcumdosew1	0.0010 1.0000 340	0.0918 0.9680 340	-0.0226 1.0000 340	0.0656 0.9999 340	0.0206 1.0000 340	0.0656 0.9999 340	-0.0345 1.0000 340
	radhlw1 avgcum~1						
radhlw1	1.0000 340						
avgcumdosew1	0.1073 1.0000 0.8298 340 340						

For males hp2vactn wave3 and d1 is not signif

Logistic regression

Number of obs = 340
 LR chi2(7) = 58.56
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.2340

Log likelihood = -95.872164

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0698089	.0169544	4.12	0.000	.0365789	.1030389
deawl	-1.031518	.5915573	-1.74	0.081	-2.190949	.1279133
shjobw1	.0185312	.0064023	2.89	0.004	.005983	.0310794
bf7m	.0000825	.0002766	0.30	0.766	-.0004597	.0006247
havmilsq	-6.78e-06	8.13e-06	-0.83	0.405	-.0000227	9.17e-06
radhlw1	.0131121	.005597	2.34	0.019	.0021422	.0240821
avgcumdosew1	-.1161641	.1842657	-0.63	0.528	-.4773183	.2449901
_cons	-7.463166	1.17919	-6.33	0.000	-9.774335	-5.151996

```

1273 .
1274 . scalar SigDoseVactnMw1 = "no"

1275 . scalar MainEffVactnMw1 = "age radhlw1 shjobw1 "

1276 .
1277 . local cn7:colnames(e(b))

1278 . di "`cn7'"
      age deaw1 shjobw1 bf7m havmilsq radhlw1 avgcumdosew1 _cons

1279 . local len7 = length("`cn7'")

1280 . di `len7'
      58

1281 . local len7b = `len7' - 6

1282 . di `len7b'
      52

1283 . local myvarlist = substr("`cn7'",1,`len7b')

1284 . di "`myvarlist'"
      age deaw1 shjobw1 bf7m havmilsq radhlw1 avgcumdosew1

1285 .
1286 . foreach var in `myvarlist' {
      2. cap gen `var'Xd1 = `var'*avgcumdosew1
      3. }

1287 .
1288 . title " Trimmed male main effects dose=> vacation plans  model"

```

```

*****                               18 Jun 2012    18:18:22    ****
> *
*****
> *
*****
> *

```

```

1289 . di as input "No sig main male dose main effects model"
      No sig main male dose main effects model

```

```

1290 . sw, pr(.1): logit hp2vacatn `myvarlist' if gender==1
              begin with full model
p = 0.7655 >= 0.1000 removing bf7m
p = 0.5322 >= 0.1000 removing avgcumdosew1
p = 0.4214 >= 0.1000 removing havmilsq

```

```

Logistic regression              Number of obs   =       340
                                LR chi2(4)       =       56.62
                                Prob > chi2       =       0.0000
Log likelihood =   -96.8403      Pseudo R2      =       0.2262

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0683746	.0168652	4.05	0.000	.0353194	.1014298
deawl	-.9608875	.5756492	-1.67	0.095	-2.089139	.1673642
shjobw1	.0175447	.0060455	2.90	0.004	.0056958	.0293937
radhlw1	.013369	.0055515	2.41	0.016	.0024883	.0242496
_cons	-7.378809	1.054557	-7.00	0.000	-9.445702	-5.311916

```

1291 .
1292 .
1293 . local cn8:colnames(e(b))

```

```

1294 . di "`cn8'"
      age deaw1 shjobw1 radhlw1 _cons

1295 . local len8 = length("`cn8'")

1296 . di `len7'
      58

1297 . local len8b = `len8' - 6

1298 . di `len8b'
      25

1299 . local myvarlist = substr("`cn8'",1,`len8b')

1300 . di "`myvarlist'"
      age deaw1 shjobw1 radhlw1

1301 .
1302 . logit hp2vacatn age radhlw1 avgcumdosew1 ageXd1 radhlw1Xd1 if gender==1

```

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -107.61459
Iteration 2:  log likelihood = -104.56768
Iteration 3:  log likelihood = -104.54823
Iteration 4:  log likelihood = -104.54822

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	41.21
	Prob > chi2	=	0.0000
Log likelihood = -104.54822	Pseudo R2	=	0.1646

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0601195	.0209224	2.87	0.004	.0191123	.1011267
radhlw1	.0187374	.0058584	3.20	0.001	.0072551	.0302197
avgcumdosew1	.1429635	3.450929	0.04	0.967	-6.620734	6.906661
ageXd1	-.0052571	.0512646	-0.10	0.918	-.1057338	.0952196
radhlw1Xd1	.0008937	.0086815	0.10	0.918	-.0161217	.0179091
_cons	-6.233448	1.294444	-4.82	0.000	-8.770513	-3.696384

```

1303 .
1304 . title "Trimmed male wave 1 interaction dose=> vacation plans model"

*****
> *
*****
> *
*****
> *
*****
> *
*****      Trimmed male wave 1 interaction dose=> vacation plans model      *****
> *
*****
> *
*****
> *
*****
> *
*****      18 Jun 2012      18:18:30      *****
> *
*****
> *
*****
> *

```

```

1305 . logit hp2vacatn age radhlw1 ageXd1 bf7m avgcumdosew1 bf4m bf4mXd1 bf7mXd1 i
> f gender==1

```

```

Iteration 0: log likelihood = -125.15243
Iteration 1: log likelihood = -102.74095
Iteration 2: log likelihood = -94.448542
Iteration 3: log likelihood = -93.949822
Iteration 4: log likelihood = -93.920677
Iteration 5: log likelihood = -93.920292
Iteration 6: log likelihood = -93.92029

```

Logistic regression	Number of obs	=	340
	LR chi2(8)	=	62.46
	Prob > chi2	=	0.0000
Log likelihood = -93.92029	Pseudo R2	=	0.2496

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0643459	.0308181	2.09	0.037	.0039435	.1247483
radhlw1	.0089983	.0057782	1.56	0.119	-.0023267	.0203233
ageXd1	-.0876104	.0995184	-0.88	0.379	-.2826628	.107442
bf7m	.0001157	.0003967	0.29	0.771	-.0006618	.0008932
avgcumdosew1	7.211044	8.155585	0.88	0.377	-8.773609	23.1957
bf4m	-.1044109	.0615606	-1.70	0.090	-.2250674	.0162456
bf4mXd1	-.1652155	.1615499	-1.02	0.306	-.4818476	.1514165
bf7mXd1	.0005521	.0007567	0.73	0.466	-.000931	.0020353
_cons	-4.176182	2.553316	-1.64	0.102	-9.18059	.8282258

Note: 1 failure and 0 successes completely determined.

```

1306 .
1307 . scalar vactnModMw1 ="none"

1308 .
1309 . title4 "Trimmed Female model wave 1 main effects dose-hp2vacatn model "

```

Trimmed Female model wave 1 main effects dose-hp2vacatn model

```

1310 . forvalues j=1/1 {
      2. local w1bf bf1 bf4 bf9 bf10 bf11 bf14m bf15m bf20 bf22 bf30 bf40
      3.
1311 . xi: logistic hp2vacatn age radhlw`j' avgcumdosew`j' ///
      > deaw`j' suchrw`j' ///
      > if gender==2, coef difficutl iterate(50)
      4.
1312 . }

```

Logistic regression	Number of obs	=	359
	LR chi2(5)	=	79.84
	Prob > chi2	=	0.0000
Log likelihood = -126.83022	Pseudo R2	=	0.2394

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0851484	.0156032	5.46	0.000	.0545668	.11573
radhlw1	.0210852	.0051434	4.10	0.000	.0110043	.031166
avgcumdosew1	.097081	.2416199	0.40	0.688	-.3764853	.5706473
deaw1	.0184403	.1587264	0.12	0.908	-.2926576	.3295383
suchrw1	.0205099	.0120186	1.71	0.088	-.0030461	.0440658
_cons	-7.695923	.966869	-7.96	0.000	-9.590951	-5.800894

```

1313 .
1314 . sw, pr(.1): logit hp2vactn age radhlw1 avgcumdosew1 havmilsq ageXd1 radhlw1X
> d1 if gender==2

```

```

begin with full model
p = 0.8147 >= 0.1000 removing havmilsq
p = 0.7305 >= 0.1000 removing avgcumdosew1
p = 0.4968 >= 0.1000 removing ageXd1
p = 0.4278 >= 0.1000 removing radhlw1Xd1

```

```

Logistic regression                                Number of obs   =       362
                                                    LR chi2(2)      =       75.57
                                                    Prob > chi2     =       0.0000
Log likelihood = -129.53941                      Pseudo R2      =       0.2258

```

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0865333	.0154134	5.61	0.000	.0563237	.116743
radhlw1	.0216968	.0050096	4.33	0.000	.0118782	.0315154
_cons	-7.711441	.9591085	-8.04	0.000	-9.591259	-5.831623

```

1315 .
1316 .
1317 .
1318 . scalar SigDoseVactnMw1 = "no"

1319 . scalar MainEffVactnMw1 = "age radhlw1"

1320 . scalar VactnModMw1 = "none"

1321 .
1322 . * summary of male moderating effects: no sign main dose effect in main effe
> cts model
1323 . *          no signif male moderators
1324 . *          3 significant main effects in main effects model
1325 .

```

```

1326 . * summary of female moderation main effects: no signif main dose effect
1327 .
1328 .
1329 . scalar SigDoseVactnFw1 = "no"

1330 . scalar MainEffVactnFw1 = "age radhlw1 bf7m"

1331 .
1332 . cap gen suchrw1Xd1 = suchrw1*avgcumdosew1

1333 .
1334 .
1335 . scalar VacatnModFw1 = "none"

1336 . *xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
    > xxxx
1337 . cap gen hp2vactn = HP2vacatn

1338 . title4 "Male mediator tests for vacation plans impact of dose"

```

```

Male mediator tests for vacation plans impact of dose

```

```

1339 . * for males
1340 .
1341 . * age is a mediator for males
1342 . glm age avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1331.608

Generalized linear models                               No. of obs      =       340
Optimization      : ML                                Residual df     =       338
                                                         Scale parameter =   148.5632
Deviance          =   50214.37624                      (1/df) Deviance =   148.5632
Pearson           =   50214.37624                      (1/df) Pearson  =   148.5632

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

Log likelihood    = -1331.607976                        AIC              =    7.844753
                                                         BIC              =   48244.19

```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	.6719789	.3966839	1.69	0.090	-.1055072	1.449465
_cons	48.89394	.6825967	71.63	0.000	47.55607	50.2318

```
1343 . 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.)

```
1344 .
```

```
1345 .
1346 . des illw1
```

variable name	storage type	display format	value label	variable label
illw1	double	%8.0g		Total number of illnesses experienced in time period 1976-1986

```
1347 . glm illw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-151.48261**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
Deviance = 48.52808533	Scale parameter	=	.1435742
Pearson = 48.52808533	(1/df) Deviance	=	.1435742
	(1/df) Pearson	=	.1435742

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

Log likelihood = -151.4826069	<u>AIC</u>	=	.9028389
	<u>BIC</u>	=	-1921.656

illw1	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew1	.0087277	.0123318		0.71	0.479	-.0154423	.0328976
_cons	.0962541	.0212201		4.54	0.000	.0546635	.1378446

```
1348 . glm hp2vactn illw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

Iteration 1: deviance = **250.8272**
 Iteration 2: deviance = **250.3035**
 Iteration 3: deviance = **250.3029**
 Iteration 4: deviance = **250.3029**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	338
Deviance = 250.3028927	Scale parameter	=	1
Pearson = 339.9984851	(1/df) Deviance	=	.7405411
	(1/df) Pearson	=	1.005913

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1719.881

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw1	-.0103789	.2018135	-0.05	0.959	-.4059261	.3851682
_cons	-1.171022	.0782871	-14.96	0.000	-1.324462	-1.017583

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

1349 .
 1350 . des radhlw1

variable name	storage type	display format	value label	variable label
radhlw1	double	%8.0g		Self-perceived Chernobyl health threat in wave 1

1351 . glm radhlw1 avgcumdosew1 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1710.3417

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1378.645
Deviance = 465981.8893	(1/df) Deviance	=	1378.645
Pearson = 465981.8893	(1/df) Pearson	=	1378.645

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

	AIC	=	10.0726
Log likelihood = -1710.341694	BIC	=	464011.7

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	2.398285	1.208412	1.98	0.047	.0298407	4.766729
_cons	44.66477	2.079384	21.48	0.000	40.58925	48.74029

```
1352 . glm hp2vactn radhlw1 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 230.8439
Iteration 2:  deviance = 224.8904
Iteration 3:  deviance = 224.6643
Iteration 4:  deviance = 224.6638
Iteration 5:  deviance = 224.6638
```

```
Generalized linear models          No. of obs      =       340
Optimization      : MQL Fisher scoring  Residual df    =       338
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 224.6638339         (1/df) Deviance = .6646859
Pearson           = 351.6837556         (1/df) Pearson  = 1.040484
```

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

```
BIC = -1745.52
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.0123039	.0020846	5.90	0.000	.0082183	.0163896
_cons	-1.857875	.1493813	-12.44	0.000	-2.150657	-1.565093

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

```
1353 .
1354 . * for females
1355 .
1356 . * age is a mediator for females
1357 . glm age avgcumdosew1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1406.325
```

```
Generalized linear models          No. of obs      =       363
Optimization      : ML              Residual df    =       361
Deviance          = 49260.25928     Scale parameter =    136.455
Pearson           = 49260.25928     (1/df) Deviance =    136.455
                                   (1/df) Pearson  =    136.455
```

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

```
Log likelihood    = -1406.325011     AIC              =    7.759366
                                   BIC              =   47132.38
```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.973879	1.117679	3.56	0.000	1.783267	6.16449
_cons	48.88157	.7187038	68.01	0.000	47.47293	50.2902

```
1358 . 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.)

```
1359 .
```

```

1360 . * illness is a mediating effect for females = > vacatn
1361 . des illw1

```

variable name	storage type	display format	value label	variable label
illw1	double	%8.0g		Total number of illnesses experienced in time period 1976-1986

```

1362 . glm illw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-259.70777**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.2462383
Deviance = 88.89203958	(1/df) Deviance	=	.2462383
Pearson = 88.89203958	(1/df) Pearson	=	.2462383

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

	<u>AIC</u>	=	1.441916
Log likelihood = -259.7077741	<u>BIC</u>	=	-2038.987

illw1	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew1	.0655142	.0474789		1.38	0.168	-.0275426	.1585711
_cons	.1570822	.0305304		5.15	0.000	.0972436	.2169207

```

1363 . glm hp2vactn illw1 if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **334.5587**
 Iteration 2: deviance = **334.5192**
 Iteration 3: deviance = **334.5191**
 Iteration 4: deviance = **334.5191**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 334.5191456	(1/df) Deviance	=	.9266458
Pearson = 363.294411	(1/df) Pearson	=	1.006356

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1793.36

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw1	.1050277	.1426608	0.74	0.462	-.1745823	.3846376
_cons	-.9602112	.0797688	-12.04	0.000	-1.116555	-.8038673

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

1364 .
 1365 . * radhlw1 is a mediating effect for females => vactn
 1366 . des radhlw1

variable name	storage type	display format	value label	variable label
radhlw1	double	%8.0g		Self-perceived Chornobyl health threat in wave 1

1367 . glm radhlw1 avgcumdosew1 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1821.9477

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	360
	Scale parameter	=	1385.301
Deviance = 498708.3025	(1/df) Deviance	=	1385.301
Pearson = 498708.3025	(1/df) Pearson	=	1385.301

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

	<u>AIC</u>	=	10.07706
Log likelihood = -1821.947718	<u>BIC</u>	=	496587.3

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	3.789972	3.562254	1.06	0.287	-3.191917	10.77186
_cons	55.44948	2.293757	24.17	0.000	50.9538	59.94516

```
1368 . glm hp2vactn radhlw1 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 302.9154
Iteration 2:  deviance = 298.4828
Iteration 3:  deviance = 298.355
Iteration 4:  deviance = 298.3548
Iteration 5:  deviance = 298.3548
```

```
Generalized linear models                                No. of obs      =       362
Optimization      :  MQL Fisher scoring                 Residual df     =       360
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 298.3548116                        (1/df) Deviance =  .8287634
Pearson           = 355.6125805                        (1/df) Pearson  =  .9878127
```

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

```
BIC = -1822.637
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.0139561	.0022604	6.17	0.000	.0095258	.0183864
_cons	-1.855913	.1776242	-10.45	0.000	-2.20405	-1.507776

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

```
1369 .
1370 . * summary of male moderating effects: no sign main dose effect in main effe
> cts model
1371 . *          no signif male moderators
1372 . *          3 significant main effects in main effects model
1373 . * summary omnibus model
1374 . des radhlw1
```

variable name	storage type	display format	value label	variable label
radhlw1	double	%8.0g		Self-perceived Chornobyl health threat in wave 1

```
1375 . glm radhlw1 avgcumdosew1 illw1 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:    log likelihood = -1818.8802
```

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	359
	Scale parameter	=	1365.815
Deviance = 490327.6005	(1/df) Deviance	=	1365.815
Pearson = 490327.6005	(1/df) Pearson	=	1365.815

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

	<u>AIC</u>	=	10.06564
Log likelihood = -1818.880199	<u>BIC</u>	=	488212.5

radhlw1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew1	4.422493	3.546316	1.25	0.212	-2.528159	11.37315
illw1	-9.71121	3.920388	-2.48	0.013	-17.39503	-2.02739
_cons	56.98053	2.359945	24.14	0.000	52.35513	61.60594

```
1376 . glm hp2vactn radhlw1 illw1 avgcumdosew1 if gender==2, fam(bin) irls scale(de
> v) link(probit)
```

```
Iteration 1:    deviance = 300.2452
Iteration 2:    deviance = 295.4656
Iteration 3:    deviance = 295.3193
Iteration 4:    deviance = 295.319
Iteration 5:    deviance = 295.319
```

Generalized linear models	No. of obs	=	362
Optimization : ML Fisher scoring	Residual df	=	358
(IRLS EIM)	Scale parameter	=	1
Deviance = 295.3190068	(1/df) Deviance	=	.8249134
Pearson = 359.0506546	(1/df) Pearson	=	1.002935

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

	BIC	=	-1813.89
--	-----	---	----------

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw1	.014364	.0022973	6.25	0.000	.0098614	.0188667
illw1	.2268401	.147174	1.54	0.123	-.0616157	.5152959
avgcumdosew1	.1252934	.1239292	1.01	0.312	-.1176035	.3681902
_cons	-1.970546	.1907882	-10.33	0.000	-2.344484	-1.596608

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

```

1377 .
1378 . scalar SigDoseVactnMw1 = "no"

1379 . scalar MainEffVactnMw1 = "age radhlw1 shjobw1 "

1380 . scalar VactnMedMw1 = "age"

1381 . scalar VactnMedFw1 = "age illw1 radhlw1"

1382 . scalar SigDoseVactnMw1 = "no"

1383 . scalar MainEffVactnMw1 = "age radhlw1"

1384 . scalar VactnModMw1 = "none"

1385 . scalar SigDoseVactnMw1 = "no"

1386 . scalar MainEffVactnMw1 = "age radhlw1"

1387 . scalar VactnModMw1 = "none"

1388 . * Part 2 Nottingham subscales
1389 . * 1: hp2work
1390 . * 2: hp2hmcare
1391 . * 3: hp2probsoc
1392 . * 4: hp2pbfhm

```

```

1393 . * 5: hp2sexlife
1394 . * 6: hp2inthob
1395 . * 7: hp2vacatn
1396 .
1397 . *xx summary of moderator effects for females:
1398 . * no signif main dose effect
1399 . * 3 signif main effects in main effect model
1400 . * 1 moderator: deawlXd1
1401 . title4 "7. Summary Matrix construction of dose - vacatn plans impact"

```

```

7. Summary Matrix construction of dose - vacatn plans impact

```

```

1402 .
1403 . matrix define vactnMw1 = J(1,8, 0)

1404 . matrix define vactnFw1 = J(1,8, 0)

1405 . matrix colnames vactnMw1= hypnum ptnum wave gender medsig numMASig numMods
> ig numMed

1406 . matrix colnames vactnFw1= hypnum ptnum wave gender medsig numMASig numMods
> ig numMed

1407 . matrix define vactnMw1= (1, 2, 1, 1, 0, 2, 0, 1 )

1408 . matrix define vactnFw1= (1, 2, 1, 2, 0, 3, 0, 3 )

1409 . matrix rowname vactnMw1 = vactnM

1410 . matrix rowname vactnFw1 = vactnF

1411 . matlist vactnMw1

```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	vactnM	1	2	1	1	0	
> 2	0	1					

```
1412 .      matlist  vactnFw1
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	vactnF	1	2	1	2	0	
> 3	0	3					

```
1413 .      matrix define H1pt2w1 = ( wkMw1 \ wkFw1 \ hmcrMw1 \ hmcrFw1 \ s
> pMw1 ///
> \ spFw1 \ prbfamMw1 \ prbfamFw1 \ sxlifemw1 \ sxlifefw1 \ inthb
> Mw1 \ inthbFw1 \ vactnMw1 \ vactnFw1 )
```

```
1414 .
```

```
1415 .      matlist H1pt2w1
```

		c1	c2	c3	c4	c5	c
> 6	c7	c8					
>							
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 1	1	2					
	r1	1	2	1	1	0	
> 2	0	1					
	r1	1	2	1	2	0	
> 2	0	2					
	spMw1	1	2	1	1	1	
> 2	2	1					
	spFw1	1	2	1	2	0	
> 5	0	2					
	prbfamMw1	1	2	1	1	0	
> 2	0	0					
	prbfamFw1	1	2	1	2	0	
> 3	0	2					
	sxlifemw1	1	2	1	1	0	
> 3	0	1					
	sxlifefw1	1	2	1	2	0	
> 4	0	5					
	inthbM	1	2	1	1	0	
> 3	0	1					
	inthobF	1	2	1	2	0	
> 3	0	4					
	vactnM	1	2	1	1	0	
> 2	0	1					
	vactnF	1	2	1	2	0	
> 3	0	3					

```

1416 .      matrix colnames H1pt2w1 =  hypnum ptnum wave gender medsig numMASig numM
      > odsig numMed

1417 .      matrix rownames H1pt2w1 =    wkMw1 wkFw1 hmcrMw1 hmcrFw1 socprbMw1
      > socprbFw1 prbfamhmMw1 prbfamhmFw1 sxlifeMw1 sxlifeFw1 inthbMw1 inthbFw1 va
      > ctnMw1 vacatnFw1

1418 .      matlist H1pt2w1

```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig	numMed					
>							
	wkMw1	1	2	1	1	0	
> 2		0	1				
	wkFw1	1	2	1	2	0	
> 1		1	2				
	hmcrMw1	1	2	1	1	0	
> 2		0	1				
	hmcrFw1	1	2	1	2	0	
> 2		0	2				
	socprbMw1	1	2	1	1	1	
> 2		2	1				
	socprbFw1	1	2	1	2	0	
> 5		0	2				
	prbfamhmMw1	1	2	1	1	0	
> 2		0	0				
	prbfamhmFw1	1	2	1	2	0	
> 3		0	2				
	sxlifeMw1	1	2	1	1	0	
> 3		0	1				
	sxlifeFw1	1	2	1	2	0	
> 4		0	5				
	inthbMw1	1	2	1	1	0	
> 3		0	1				
	inthbFw1	1	2	1	2	0	
> 3		0	4				
	vactnMw1	1	2	1	1	0	
> 2		0	1				
	vacatnFw1	1	2	1	2	0	
> 3		0	3				

```

1419 .    set more off

1420 .    scalar list
MainEffVactnMw1 = age radhlw1
sxlifeMedMw1 = radhlw1
MainEffsxlifeFw1 = age bf4 bf4m
SigDoseSxlifeFw1 = no
MainEffhmcFw1 = age
MainEffhmcMw1 = age
hmcMedFw1 = age bf4
hmcMedMw1 = radhlw1
MainEffwkFw1 = age
MainEffwkMw1 = age
VactnMedFw1 = age illw1 radhlw1
VactnMedMw1 = age
VactnModFw1 = none
MainEffVactnFw1 = age radhlw1 bf7m
SigDoseVactnFw1 = no
VactnModMw1 = none
inthobMedFw1 = age bf4 illw1 bf4m
inthobMedMw1 = age
    inthobMw1 = age
InthbModFw1 = none
MainEffInthbFw1 = age radhlw1 bf4
SigDoseInthbFw1 = no
InthbModMw1 = none
MainEffInthbMw1 = age radhlw1 shfamw1
SigDoseInthbMw1 = no
MainEffMw1 = radhlw1 bf4 bf40
sxlifeMedFw1 = age illw1 radhlw1 bf4 bf4m
SigDosesxlifeMw1 = no
MainEffsxlifeMw1 = age bf4 bf40
SigDosePrbfmhmMw1 = no
vactnModMw1 = none
SigDoseVactnMw1 = no
SxLifeModFw1 = no
sxlifeModFw1 = none
sxlifeModMw1 = none
MaineffhmcMw1 = age bf4 bf40
SigDoseMEhmcMw1 = no
PrbfmhmMedFw1 = age bf4
PrbfmhmMedMw1 = age
MainEffPrbfmhmFw1 = age radhlw1 bf4
MainEffPrbfmhmMw1 = age bf4
PrbfmhmModFw1 = none
PrbfmhmModMw1 = none
SigDosePrbfmhmFw1 = no
SigDosePrbfhmMw1 = no
MainEffPrbfhmMw1 = age bf4

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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
MainEffPrbsocMw1 = age bf4m
SigdoseMw1 = no
ProbsocMedFw1 = age bf4
ProbsocMedMw1 = radhlw1
ProbsocModFw1 = none
SigDoseProbsocMw1 = no
hmcrmedMw1 = radhlw1
hmcrmedFw1 = age b4 b40
SigdosehmcrFw1 = no
MainEffProbSocFw1 = age radhlw1 avgcumdosew1 shrelaw1 bf4
SigDoseProbsocFw1 = yes
PrbsocModMw1 = shjobw1Xd1 shrelaw1Xd1
    WkhmcrMw1 = age b4
    WkModFw1 = ageXd1
hmcareMedFw1 = age illw1
hmcareMedMw1 = age
SigDosehmcrFw1 = no
    wkMedMw1 = bf40
hmcrModFw1 = none
SigDoseHmcrFw1 = yes
    WkMedMw1 = bf40
hmcrModMw1 = none
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
VactnMedMw2 = 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

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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

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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

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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

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```

1421 . pwd
      /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/h1tests/h1pt2

1422 . di c(filename)
      chwide16june2012.dta

1423 .
1424 . sjlog close, replace

```