Advanced Methods in Health Services Research: Analysis - 309.716 Tuesday and Thursday 9:00-10:20 Instructors: Darrell J. Gaskin, Ph.D. Roland J. Thorpe, Ph.D. 250 Hampton House

Computer Exercise #4: Estimating the Effect of Sex and Race/Ethnicity on having an office based physician visit using LPM, Logistic, and Probit Regression Models

Due: September 27, 2016

Answer Guide/Suggested Answers

1. Consider the following model

Hospital Readmissions = B₀ + B₁*Pct_Medicare_Patients + B₂ Teach_Hospital + B₃ Pct Medicare Patient*Teach Hospital

a. What is the marginal effect of percentage of Medicare patients on the number of readmissions?

The marginal effect can be taken by computing the partial derivative of Readmissions with respect to Pct_Medicare_Patient:

$$\frac{\partial Readmissions}{\partial Pct\ Medicare\ Patient} = \beta_1 + \beta_3 * Teach_Hospital$$

We see here that the marginal effect of the percentage of Medicare patients is β_1 if the hospital is not a teaching hospital and $\beta_1 + \beta_3$ if the hospital is a teaching hospital.

b. What is the marginal effect of being a teaching hospitals on the number of readmissions?

The marginal effect can be taken by computing the partial derivative of Readmissions with respect to Teach Hospital:

$$\frac{\partial Readmissions}{\partial Teach_Hospital} = \beta_2 + \beta_3 * Pct_Medicare_Patient$$

We see here that the marginal effect of the percentage of Medicare patients is β_2 + β_3 *(percentage of Medicare patients).

c. What does B3 tell us?

 β_3 gives us the interaction effect between Pct_Medicare_Patient or the percentage of Medicare patients and Teach_Hospital or being a teaching hospital. That is, we can interpret β_3 as the additional effect of changes in the percentage of Medicare patients on readmissions if the hospital is a teaching hospital. Alternatively, we can also interpret β_3 as the additional effect of being a teaching hospital on readmissions at different levels of the percentage of Medicare patients.

Use the analysis file you built in computer exercises 1-3. For this analysis, limit the sample to adults, i.e., persons over the age of 17. Note you will have to create a variable that identifies the adult sample. Use the subpop command with the svy procedures to estimate the models correctly in Stata.

Using the office based physician variable *obtotv08* create a dummy variable indicating if a person had an office based physician visit during the year.

Create sex-insurance status interaction variables

Create sex-insurance categorical variables (male private insured, female private insured, male Medicare insured, female Medicare insured, male Medicaid-other public insured, female Medicaid-other public insured, male uninsured, female uninsured)

2. Estimate the following models using linear probability model (LPM) and logistic regression techniques.

Model 1: Any obvisit = f(age, race/ethnicity, sex, poverty status, education, insurance status, **sex-insurance status interaction**, health status, MSA status and region)

a. Create table 1 that displays the model 1 coefficients for LPM regressions the sex and insurance variables and interpret the coefficients for LPM.

TABLE 1. LPM Coefficients, Model 1

	(1)
	LPM
Public Insurance	0.00361
	(0.0250)
Uninsured	-0.241***
	(0.0176)
Medicare	0.0699***
	(0.0147)

Female	0.147***
	(0.00728)
	(0.00728)
Public Insurance-Female	0.0438
Tuone insurance Temale	
	(0.0241)
Lluingamed Female	0.0121
Uninsured-Female	-0.0121
	(0.0211)
	2 2 2 2 2 ***
Medicare-Female	-0.0889***
	(0.0152)
N	31258
R^2	0.206

Standard errors in parentheses p < 0.05, ** p < 0.01, *** p < 0.001

The coefficients on Female represents the main effect of gender. The coefficient implies that being female increases the predicted probability of having any office visit by 0.147 compared to being male, holding all other things constant. We also note that it is the effect of being female and having private insurance.

The coefficients on public insurance, uninsured, and Medicare, represent the effect of having these types of insurance on the predicted probability of having any office relative to having private insurance. We note that for men, these are the only effects of insurance status on their predicted probabilities. From above, the regression results imply that for men, being uninsured decreases the probability of having any physician office visit by -0.241 and being on Medicare increases the probability by 0.0699 compared to having private insurance, holding all other things constant. Both are statistically significant. The effect of Medicaid/public insurance was not statistically significant. To examine the effect of insurance status conditional on being female, we have to account for the gender/interaction term.

The interaction terms represent the modification of the effect of insurance status due to gender. In particular, in our case it represents the modification of the effect of insurance status on the predicted probability of having an office visit conditional on being female. The coefficient on Medicare*Female, for example, implies that females on Medicare decreases have 0.0889 lower probability of an office visit compared to men on Medicare. Thus for females, being on Medicare decreases the probability of an office visit by 0.0699 (coefficient on Medicare) – 0.0889 (coefficient on Medicare*Female) = 0.019 compared to having private insurance. Additionally, we note that women on Medicare have 0.147 + 0.0699 (the coefficient on Medicare) - 0.0889 (the coefficient on Medicare*Female) = 0.128 higher probability of having any office visit compared to privately insured men. The other interaction variables can be interpreted similarly but are not statistically significant.

b. Create table 2 that displays the model 1 coefficients and odds ratios for the logistic regression model.

TABLE 2. Logit Coefficients and Odds Ratios, Model 1

	(1)	(2)
	Coefficients	OR
obtotv08n		
Public Insurance	0.119	1.126
	(0.121)	(0.136)
Uninsured	-0.966***	0.381***
	(0.0860)	(0.0327)
Medicare	0.238	1.269
	(0.138)	(0.175)
Female	0.951***	2.589***
	(0.0497)	(0.129)
Public Insurance-Female	0.0800	1.083
	(0.127)	(0.137)
Uninsured-Female	-0.367***	0.693***
	(0.106)	(0.0736)
Medicare-Female	-0.270	0.763
	(0.168)	(0.128)
N	31258	31258

Standard errors in parentheses

c. Discuss the problems associated with interpreting the coefficients on the sex and insurance status interaction variables.

The main problem is that the coefficients on the sex/insurance status interaction variables cannot be interpreted by themselves. As we saw in (a), we have to add coefficients to deduce the effects of belonging to different categories relative to the base categories. Thus it would be more difficult for consumers of the analysis to interpret the results of the regression. In addition, it would be more difficult to ascertain significant differences between groups when we add the pertinent coefficients as some coefficients are significant while others are not. The problem of interpretation is even more acute for logit models. Adding changes in log odds or odds ratios does not make for a convenient interpretation of the results.

^{*} p < 0.05, ** p < 0.01, *** p < 0.001

Model 2: Any obvisit = f(age, race/ethnicity, **sex-insurance status categories**, poverty status, education, health status, MSA status and region) *Use males with private insurance as the reference group*.

d. Create table 3 that displays the model 2 coefficients for LPM regressions for the sex and insurance status variables.

TABLE 3. LPM Coefficients, Model 2

TABLE 3. LPM Coefficients, Model 2	
Private Insurance - Women	(1) LPM 0.147*** (0.00728)
Public Insurance - Men	0.00361 (0.0250)
Public Insurance - Women	0.195*** (0.0156)
Uninsured - Men	-0.241*** (0.0176)
Uninsured - Women	-0.105*** (0.0181)
Medicare - Men	0.0699*** (0.0147)
Medicare - Women	0.128*** (0.0118)
$\frac{N}{R^2}$	31258 0.206

Standard errors in parentheses p < 0.05, p < 0.01, p < 0.001

e. Interpret the coefficients for LPM.

Here, the interpretations of the coefficients are more straightforward. We recall that we set the base category as men with private insurance. Thus the coefficients on the different sex/insurance status categories represent the change or the difference in the predicted probabilities of having an office visit of the different categories compared to males with private insurance. As an example, women on private insurance have 0.147 higher probability of having an office visit compared to men on private insurance. Similarly, uninsured women have a 0.105 lower probability of an office visit compared to men on private insurance.

The other coefficients can be interpreted accordingly. All coefficients except for that on men with public insurance are statistically significant.

f. Create table 4 that displays the model 2 coefficients for the logistic regression model for the sex and insurance status variables.

TABLE 4. Logit Coefficients and Odds Ratios, Model 2

	(1)	(2)
	Coefficients	OR
obtotv08n		
Private Insurance - Women	0.951***	2.589***
	(0.0497)	(0.129)
Public Insurance - Men	0.119	1.126
	(0.121)	(0.136)
Public Insurance - Women	1.150***	3.158***
	(0.102)	(0.323)
Uninsured - Men	-0.966***	0.381***
	(0.0860)	(0.0327)
Uninsured - Women	-0.382***	0.683***
	(0.0843)	(0.0576)
Medicare - Men	0.238	1.269
	(0.138)	(0.175)
Medicare - Women	0.920***	2.508***
	(0.160)	(0.400)
N	31258	31258

Standard errors in parentheses p < 0.05, p < 0.01, p < 0.001

> g. Interpret the coefficients on the sex and insurance status variables. Do the coefficients from Model 2 present the same problems as those from Model 1? Why or why not?

We interpret the odds ratios as these are more convenient to interpret. From Table 4, we see that the odds of having any office visit for women on private insurance is 2.589 times that of the odds for men on private insurance, holding all other variables constant. We also note that the odds of having any office visit for women on public insurance is 3.158 times that of the odds for men on private insurance. The other coefficients can be interpreted similarly.

The problems we saw with model 1 are no longer present here since we can directly interpret the coefficients on the different categories as opposed to adding the different coefficients for the different variables we used in model 1.

name: <unnamed>

log: /Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/Answers/Assignment4 2016.lo

> g

log type: text

opened on: 4 Oct 2016, 15:47:42

. use "/Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/meps08.dta", replace

. cd "/Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/Answers" /Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/Answers

. svyset varpsu [pweight = perwt08f], strata(varstr)

. /*Variable Creation and Cleaning*/

. * Trimming the data

. summ totexp08

Variable | Obs Mean Std. Dev. Min Max
-----totexp08 | 33066 3142.069 9786.619 0 553493

. summ totexp08, detail

total health care exp 08

	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	33066
25%	67	0	Sum of Wgt.	33066
50%	528.5		Mean	3142.069
		Largest	Std. Dev.	9786.619
75%	2425	238659		
90%	7453	264510	Variance	9.58e+07
95%	13582	373799	Skewness	14.40863
99%	40763	553493	Kurtosis	469.447

. gen healthexp = totexp08

. replace healthexp = . if totexp08 < 0 /*replaces negative values with missing*/ (0 real changes made) $\,$

. replace healthexp = . if totexp08 > 100000 /*replaces values > \$100,000 with missing*/ $$\rm \sim 100000~\rm cm^{-3}$

(42 real changes made, 42 to missing)

. summ healthexp

Variable	1	Obs	Mean	Std.	Dev.	Min	Max
healthexp	+	33024	2937.216	7412	.106	0	99988

. summ healthexp, detail

		X.	

	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	33024
25%	66	0	Sum of Wgt.	33024
50%	526		Mean	2937.216
		Largest	Std. Dev.	7412.106
75%	2413.5	98210		
90%	7353	99251	Variance	5.49e+07
95%	13387	99264	Skewness	5.819768
99%	38550	99988	Kurtosis	48.38959

•

- . gen income = ttlp08x
- . replace income = . if ttlp08x < 0 /*sets negative values to missing*/ (25 real changes made, 25 to missing)
- . replace income = . if ttlp08x > 170000 /*sets very large values to missing*/ (325 real changes made, 325 to missing)
- . /* Note: If you did not exclude those with incomes > 170000, it's fine*/ $\dot{}$
- . summarize income

Variable	Obs	Mean	Std. Dev.	Min	Max
	·				
income	32716	18715.83	24109.08	0	169564

. summarize income, detail

income

	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	32716
25%	0	0	Sum of Wgt.	32716
50%	10000		Mean	18715.83
		Largest	Std. Dev.	24109.08
75%	28838	164895		
90%	52000	164895	Variance	5.81e+08
95%	70000	165391	Skewness	1.717878
99%	103084	169564	Kurtosis	6.147364

- . * Generate Categories
- . gen age18over = 0

. replace age18over = 1 if age08x >= 18 (23183 real changes made)

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```
. gen agecat = 1 if age08x \geq=0 & age08x \leq=17
(23434 missing values generated)
. replace agecat = 2 if age08x \geq18 & age08x \leq24
(3372 real changes made)
. replace agecat = 3 if age08x >=25 & age08x <=44
(8813 real changes made)
. replace agecat = 4 if age08x >=45 \& age08x <=64
(7614 real changes made)
. replace agecat = 5 if age08x >=65 & age08x <=74
(1867 real changes made)
. replace agecat = 6 if age08x >=75
(1517 real changes made)
. label define agecats 1 "0-18" 2 "18-24" 3 "25-44" 4 "45-64" 5 "65-74" 6 "75+"
. label values agecat agecats /*set label name sexn to the variable sex*/
. tabulate agecat
    agecat | Freq. Percent
     0-18 | 9,632 29.35 29.35
18-24 | 3,372 10.28 39.63
     18-24 I
     25-44 | 8,813 26.86 66.48

45-64 | 7,614 23.20 89.69

65-74 | 1,867 5.69 95.38

75+ | 1,517 4.62 100.00
-----
     Total | 32,815 100.00
. gen race = 1 if racex == 1 & racethnx != 1
(18775 missing values generated)
. replace race = 2 if racex == 2 & racethnx != 1
(6476 real changes made)
. replace race = 3 if racethnx == 1
(9392 real changes made)
. replace race = 4 if racex == 4 & racethnx != 1
(1997 real changes made)
. replace race = 5 if (racex == 3 | racex == 5 | racex == 6) & racethnx != 1
(910 real changes made)
. label define racexn2 1 "White" 2 "Black" 3 "Hispanic" 4 "Asian" 5 "Other"
. label values race racexn2
. label define sexn 1 "male" 2 "female"
```

. label values sex sexn

. tabulate sex

```
sex | Freq. Percent
-----
    male | 15,885 48.04 female | 17,181 51.96
                                        48.04
                                       100.00
     Total | 33,066 100.00
. gen female = 0 if sex == 1
(17181 missing values generated)
. replace female = 1 if sex == 2
(17181 real changes made)
. gen racesexcat = 1 if race == 1 & female == 0
(26095 missing values generated)
. replace racesexcat = 2 if race == 1 & female == 1
(7320 real changes made)
. replace racesexcat = 3 if race == 2 & female == 0
(2894 real changes made)
. replace racesexcat = 4 if race == 2 & female == 1
(3582 real changes made)
. replace racesexcat = 5 if race == 3 & female == 0
(4612 real changes made)
. replace racesexcat = 6 if race == 3 & female == 1
(4780 real changes made)
. replace racesexcat = 7 if race == 4 & female == 0
(965 real changes made)
. replace racesexcat = 8 if race == 4 & female == 1
(1032 real changes made)
. replace racesexcat = 9 if race == 5 \& female == 0
(443 real changes made)
. replace racesexcat = 10 if race == 5 & female == 1
(467 real changes made)
. gen whitemale = 0 /*okay since no missings for race and sex*/
. replace whitemale = 1 if race == 1 & female == 0
(6971 real changes made)
. gen whitefemale = 0
. replace whitefemale = 1 if race == 1 & female == 1
(7320 real changes made)
. gen blackmale = 0
. replace blackmale = 1 if race == 2 & female == 0
(2894 real changes made)
```

```
. gen blackfemale = 0
. replace blackfemale = 1 if race == 2 & female == 1
(3582 real changes made)
. gen hispanicmale = 0
. replace hispanicmale = 1 if race == 3 & female == 0
(4612 real changes made)
. gen hispanicfemale = 0
. replace hispanicfemale = 1 if race == 3 & female == 1
(4780 real changes made)
. gen asianmale = 0
. replace asianmale = 1 if race == 4 & female == 0
(965 real changes made)
. gen asianfemale = 0
. replace asianfemale = 1 if race ==4 & female == 1
(1032 real changes made)
. gen othermale = 0
. replace othermale = 1 if race == 5 \& female == 0
(443 real changes made)
. gen otherfemale = 0
. replace otherfemale = 1 if race == 5 & female == 1
(467 real changes made)
. label define racesex 1 "White Male" 2 "White Female" 3 "Black Male" 4 "Black Female"
5 "Hispanic Male" 6 "
> Hispanic Female" 7 "Asian Male" 8 "Asian Female" 9 "Other Male" 10 "Other Female"
. label values racesexcat racesex
. gen healthstatus = 1 if rthlth42 == 1
(23215 missing values generated)
. replace healthstatus = 2 if rthlth42 == 2
(10188 real changes made)
. replace healthstatus = 3 if rthlth42 == 3
(8628 real changes made)
. replace healthstatus = 4 if rthlth42 == 4
(2777 real changes made)
. replace healthstatus = 5 if rthlth42 == 5
(815 real changes made)
. label define health 1 "Excellent" 2 "Very Good" 3 "Good" 4 "Fair" 5 "Poor"
. label values healthstatus health
```

```
. gen education = 1 if educyr >=0 & educyr <=8
(25465 missing values generated)
. replace education = 2 if educyr >=9 & (educyr <=12 & educyr >=0) & hideg == 1
(3732 real changes made)
. replace education = 3 if hideg == 2 | hideg == 3
(11173 real changes made)
. replace education = 4 if educyr >=13 \& educyr <=17 \& hideg == 3
(3629 real changes made)
. replace education = 5 if hideg == 4
(3245 real changes made)
. replace education = 6 if hideg == 5 | hideg == 6
(1590 real changes made)
. label define educ 1 "Grade 8 and below" 2 "Some High School" 3 "HighSchool" 4 "Some
College" 5 "College" 6
> "Advanced Degree"
. label values education educ
. gen insurance = 1 if inscov08 == 1
(14773 missing values generated)
. replace insurance = 2 if inscov08 == 2 & mcrev08 == 2
(6642 real changes made)
. replace insurance = 3 if inscov08 == 3
(5662 real changes made)
. replace insurance = 4 if inscov08 == 2 & mcrev08 == 1
(2469 real changes made)
. label define insure 1 "Private Ins" 2 "Medicaid" 3 "Uninsured" 4 "Medicare"
. label values insurance insure
. gen inssexcat = 1 if insurance == 1 & female == 0
(24151 missing values generated)
. replace inssexcat = 2 if insurance == 1 & female == 1
(9378 real changes made)
. replace inssexcat = 3 if insurance == 2 & female == 0
(2953 real changes made)
. replace inssexcat = 4 if insurance == 2 & female == 1
(3689 real changes made)
. replace inssexcat = 5 if insurance == 3 & female == 0
```

```
(3008 real changes made)
. replace inssexcat = 6 if insurance == 3 & female == 1
(2654 real changes made)
. replace inssexcat = 7 if insurance == 4 & female == 0
(1009 real changes made)
. replace inssexcat = 8 if insurance == 4 & female == 1
(1460 real changes made)
. label define insex 1 "Priv Ins Men" 2 "Priv Ins Women" 3 "Medicaid Men" 4 "Medicaid
Women" 5 "Uninsured Me
> n" 6 "Uninsured Women" 7 "Medicare Men" 8 "Medicare Women"
. label values inssexcat insex
. gen region = 1 if region08 == 1
(28080 missing values generated)
. replace region = 2 if region 08 == 2
(6499 real changes made)
. replace region = 3 if region 08 == 3
(12424 real changes made)
. replace region = 4 if region 08 == 4
(8906 real changes made)
. label define region2 1 "Northeast" 2 "Midwest" 3 "South" 4 "West"
. label values region region2
. gen fpl = 1 if povcat08 == 1
(26099 missing values generated)
. replace fpl = 2 if povcat08 == 2
(2171 real changes made)
. replace fpl = 3 if povcat08 == 3
(5667 real changes made)
. replace fpl = 4 if povcat08 == 4
(9595 real changes made)
. replace fpl = 5 if povcat08 == 5
(8666 real changes made)
. label define fplstat 1 "Poor" 2 "Near Poor" 3 "Low Income" 4 "Middle Income" 5 "High
Income"
. label values fpl fplstat
. gen notmsa = 1 if msa08 == 0
(28406 missing values generated)
```

```
. replace notmsa = 0 if msa08 == 1
(28155 real changes made)
. gen obtotv08n = 0 if obtotv08 == 0
(22054 missing values generated)
. replace obtotv08n = 1 if obtotv08 >=1
(22054 real changes made)
. /*Number 2*/
. *help fvvarlist
. ** Model 1
. * Linear Probability Model
. svy, subpop(age18over): reg obtotv08n ib1.insurance##sex i.healthstatus ib3.agecat
i.race ///
> ib5.fpl ib3.education notmsa ib1.region
(running regress on estimation sample)
Survey: Linear regression
Number of strata = 165
Number of PSUs = 370
                                                        Number of obs =
                                                          Population size = 284307457
Number of PSUs
                               370
                                                          Subpop. no. of obs = 20107
                                                          Subpop. size = 207295725

Design df = 205

F( 32, 174) = 173.38

Prob > F = 0.0000
                                                          R-squared
                                                                                =
                                                                                        0.2064
   ._____
         | Linearized obtotv08n | Coef. Std. Err.
                                                        t P>|t| [95% Conf. Interval]
______
           insurance |
          Medicaid | .0036096 .0250178 0.14 0.885 -.0457156 .0529348
          Uninsured | -.2405578 .0176057 -13.66 0.000 -.2752693 -.2058464
          Medicare | .0698667 .0147064
                                                        4.75 0.000
                                                                             .0408715 .0988618
                 sex |
             female | .1472871 .0072804 20.23 0.000 .132933 .1616412
      insurance#sex |

      Medicaid#female | .0437597
      .0241271
      1.81
      0.071
      -.0038094

      Uninsured#female | -.012076
      .0211177
      -0.57
      0.568
      -.0537118

      Medicare#female | -.0888763
      .0151969
      -5.85
      0.000
      -.1188386

  Medicaid#female |
                                                                                            .0913288
                                                                                           .0295598
                                                                                              -.058914
       healthstatus |

      .0737853
      .0105081
      7.02
      0.000
      .0530675
      .094503

      .1159634
      .0113728
      10.20
      0.000
      .0935408
      .1383859

      .2015123
      .0123947
      16.26
      0.000
      .1770749
      .2259496

      .2521038
      .0154487
      16.32
      0.000
      .2216451
      .2825625

          Very Good |
                Good I
                Fair |
               Poor |
               agecat |
```

65-74 75+	.162363 .189536	.0116351	13.95 16.22	0.000	.1394231	.1853029 .2125767
race	[
Black	 1178243	.0103882	-11.34	0.000	1383058	0973428
Hispanic	1150025	.01331188	-8.77	0.000	1408676	0891373
Asian	1407749	.0161656	-8.71	0.000	172647	1089028
Other	032871	.0346938	-0.95	0.345	1012734	.0355313
6.3						
fpl		0101150	4 01	0 000	0000010	0000500
Poor	0565723	.0134472	-4.21	0.000	0830849	0300598
Near Poor	0510409	.0181924	-2.81	0.006	0869091	0151727
Low Income	0391438	.0113795	-3.44	0.001	0615798	0167079
Middle Income	0371092	.0098996	-3.75	0.000	0566273	0175912
education						
Grade 8 and below	.0024143	.0155315	0.16	0.877	0282076	.0330363
Some High School	0162994	.0117257	-1.39	0.166	0394178	.006819
Some College	.0488912	.0096691	5.06	0.000	.0298276	.0679547
College	.0901982	.0099331	9.08	0.000	.0706141	.1097823
Advanced Degree	.103468	.0126997	8.15	0.000	.0784293	.1285068
notmsa	 0135874	.0088065	-1.54	0.124	0309502	.0037754
region	 					
Midwest	.0003883	.0115426	0.03	0.973	0223691	.0231458
South	0122769	.0100813	-1.22	0.225	0321532	.0075993
West	0192716	.0110263	-1.75	0.082	041011	.0024678
_cons	 .5879307	.0151007	38.93	0.000	.5581581	.6177033

. eststo lpm

. * Logit regression

. svy, subpop(age18over): logit obtotv08n ib1.insurance##sex i.healthstatus ib3.agecat i.race i.sex ///

Survey: Logistic regression

> ib5.fpl ib3.education notmsa ib1.region
(running logit on estimation sample)

insurance#sex	 					
Medicaid#female	.0799721	.1267309	0.63	0.529	169891	.3298352
Uninsured#female	3674104	.1062548	-3.46	0.001	5769027	1579181
Medicare#female	2699952	.1680248	-1.61	0.110	6012735	.061283
healthstatus	 					
Very Good	.4127457	.0589983	7.00	0.000	.2964245	.5290669
Good	.6793008	.0666499	10.19	0.000	.5478937	.810708
Fair	1.370507	.0898606	15.25	0.000	1.193337	1.547676
Poor	2.15732	.1987641	10.85	0.000	1.765436	2.549204
agecat	 					
18-24	0595924	.0685782	-0.87	0.386	1948013	.0756165
45-64	.4947306	.0562597	8.79	0.000	.3838089	.6056524
65-74	1.23893	.1173271	10.56	0.000	1.007608	1.470253
75+	1.785625	.1639472	10.89	0.000	1.462386	2.108864
race	 					
Black	6944178	.0586745	-11.84	0.000	8101007	578735
Hispanic	6218349	.0717762	-8.66	0.000	763349	4803207
Asian	8599299	.0855788	-10.05	0.000	-1.028657	6912025
Other	2511919	.2096103	-1.20	0.232	6644603	.1620766
fpl						
Poor	36992	.0816197	-4.53	0.000	5308418	2089982
Near Poor	3545885	.1162897	-3.05	0.003	5838656	1253113
Low Income	2624286	.0725383	-3.62	0.000	4054454	1194119
Middle Income	2496556	.0621756	-4.02	0.000	3722413	12707
education	 					
Grade 8 and below	0393499	.1030583	-0.38	0.703	24254	.1638402
Some High School	0955722	.0679421	-1.41	0.161	229527	.0383827
Some College	.2877786	.0604707	4.76	0.000	.1685543	.4070029
College	.5670646	.0680307	8.34	0.000	.432935	.7011942
Advanced Degree	.696993	.0995001	7.00	0.000	.5008182	.8931678
notmsa	1003801	.0593549	-1.69	0.092	2174044	.0166442
region	 					
Midwest	0095235	.0781824	-0.12	0.903	1636683	.1446212
South	0830117	.0682538	-1.22	0.225	2175811	.0515578
West	12984	.0734891	-1.77	0.079	2747315	.0150514
_cons	.2607229	.0860613	3.03	0.003	.0910441	.4304017

[.] eststo logit1

Survey: Logistic regression

Number of strata	=	165	Number of obs =	=	31258
Number of PSUs	=	370	Population size =	=	284307457
			Subpop. no. of obs =	=	20107
			Subpop. size =	=	207295725
			Design df =	=	205

[.] svy, subpop(age18over): logit obtotv08n ib1.insurance##sex i.healthstatus ib3.agecat i.race i.sex ///

i.race i.sex ///
> ib5.fpl ib3.education notmsa ib1.region, or
(running logit on estimation sample)

obtotv08n	 Odds Ratio	Linearized Std. Err.	t	P> t	[95% Conf.	Interval]
	+					
insurance	1 10001	1260040	0 00	0 207	007076	1.428979
Medicaid	1.12601	.1360848	0.98	0.327	.887276	
Uninsured Medicare	.3807233 1.269127	.0327282 .1747816	-11.23 1.73	0.000	.3213682 .9673492	.4510411 1.665049
Medicare	1.269127	.1/4/816	1.73	0.085	.96/3492	1.003049
sex	ĺ					
female	2.588844	.1285448	19.16	0.000	2.347415	2.855104
insurance#sex	İ					
Medicaid#female	1.083257	.1372821	0.63	0.529	.8437568	1.390739
Uninsured#female	.6925254	.0735841	-3.46	0.001	.5616352	.8539198
Medicare#female	.7633831	.1282673	-1.61	0.110	.5481132	1.0632
healthstatus	 					
Very Good	1.510961	.089144	7.00	0.000	1.345041	1.697348
Good	1.972498	.1314668	10.19	0.000	1.729606	2.2495
Fair	3.937345	.3538124	15.25	0.000	3.298069	4.700535
Poor	8.64793	1.718898	10.85	0.000	5.844119	12.79691
agecat						
18-24	.9421485	.0646108	-0.87	0.386	.8229981	1.078549
45-64	1.640056	.092269	8.79	0.000	1.467865	1.832447
65-74	3.451919	.4050037	10.56	0.000	2.739041	4.350335
75+	5.963304	.9776669	10.89	0.000	4.316246	8.238873
race	 					
Black	.4993651	.0293	-11.84	0.000	.4448133	.5606071
Hispanic	.5369583	.0385408	-8.66	0.000	.4661028	.618585
Asian	.4231917	.0362162	-10.05	0.000	.3574866	.5009733
Other	.7778731	.1630502	-1.20	0.232	.5145512	1.17595
fpl	 					
Poor	.6907896	.0563821	-4.53	0.000	.5881097	.8113967
Near Poor	.7014621	.0815728	-3.05	0.003	.5577382	.8822222
Low Income	.7691813	.0557951	-3.62	0.000	.6666798	.8874422
Middle Income	.779069	.0484391	-4.02	0.000	.689188	.880672
education	 					
Grade 8 and below	.9614142	.0990817	-0.38	0.703	.7846324	1.178026
Some High School	.9088528	.0617493	-1.41	0.161	.7949095	1.039129
Some College	1.333462	.0806354	4.76	0.000	1.183592	1.502308
College	1.763084	.1199439	8.34	0.000	1.541776	2.016159
Advanced Degree	2.007706	.1997671	7.00	0.000	1.650071	2.442856
notmsa	.9044935	.0536861	-1.69	0.092	.8046045	1.016783
region						
Midwest	.9905217	.0774414	-0.12	0.903	.8490236	1.155602
South	.9203404	.0628167	-1.22	0.225	.8044624	1.05291
West	.8782359	.0645408	-1.77	0.079	.7597761	1.015165
_cons	1.297868	.1116962	3.03	0.003	1.095317	1.537875

[.] eststo logit2

```
. * Table 1
. esttab lpm using hw4table1.rtf , se r2 replace keep(2.sex 2.insurance 3.insurance
4.insurance 2.insurance#
> 2.sex ///
   3.insurance#2.sex 4.insurance#2.sex) mtitles(LPM) coeflabels(2.sex
2.insurance "Public Insurance" /
> 3.insurance Uninsured 4.insurance Medicare 2.insurance#2.sex "Public Insurance-
Female" ///
> 3.insurance#2.sex "Uninsured-Female" 4.insurance#2.sex "Medicare-Female") ///
> title(TABLE 1. LPM Coefficients, Model 1)
(output written to hw4table1.rtf)
. * Table 2
. esttab logit1 logit2 using hw4table2.rtf , se r2 replace keep(2.sex 2.insurance
3.insurance 4.insurance 2.
> insurance#2.sex ///
> 3.insurance#2.sex 4.insurance#2.sex) mtitles(Coefficients OR) coeflabels(2.sex
Female 2.insurance "Public
> Insurance" ///
> 3.insurance Uninsured 4.insurance Medicare 2.insurance#2.sex "Public Insurance-
Female" ///
> 3.insurance#2.sex "Uninsured-Female" 4.insurance#2.sex "Medicare-Female") ///
> title(TABLE 2. Logit Coefficients and Odds Ratios, Model 1) eform(0 1)
(output written to hw4table2.rtf)
. ** Model 2
. * Linear Probability Model
. svy, subpop(age18over): reg obtotv08n ib1.inssexcat ib1.healthstatus ib3.agecat
i.race ///
> ib5.fpl ib3.education notmsa ib1.region
(running regress on estimation sample)
Survey: Linear regression
Number of strata = 165
Number of PSUs = 370
                                                                =
                                              Number of obs
                                                                       31258
                                              Population size = 284307457
                                              Subpop. no. of obs = 20107
                                              Subpop. size = 207295725
Design df = 205
                                              F( 32, 174) = Prob > F = R-squared =
                                                                      173.38
                                                                      0.0000
                                              R-squared
                                                                      0.2064
______
        obtotv08n | Coef. Std. Err.
                                              t P>|t| [95% Conf. Interval]
        inssexcat |
   Priv Ins Women | .1472871 .0072804 20.23 0.000 .132933 .1616412 Medicaid Men | .0036096 .0250178 0.14 0.885 -.0457156 .0529348 Medicaid Women | .1946564 .0155975 12.48 0.000 .1639043 .2254085 Uninsured Men | -.2405578 .0176057 -13.66 0.000 -.2752693 -.2058464
   Priv Ins Women |
  Medicaid Women |
  Uninsured Women | -.1053468 .0180801 -5.83 0.000 -.1409936 -.0696999
    Medicare Men | .0698667 .0147064
                                             4.75 0.000 .0408715 .0988618
  Medicare Women | .1282775 .011826 10.85 0.000
                                                              .1049613 .1515937
     healthstatus |
       Very Good | .0737853 .0105081 7.02 0.000 .0530675 .094503
```

Good	.1159634	.0113728	10.20	0.000	.0935408	.1383859
Fair	.2015123	.0123947	16.26	0.000	.1770749	.2259496
Poor	.2521038	.0154487	16.32	0.000	.2216451	.2825625
FOOL	.2321030	.0134407	10.32	0.000	.2210431	.2023023
agecat	! 					
18-24	0258016	.0134958	-1.91	0.057	05241	.0008068
45-64	.0869574	.0091178	9.54	0.000	.0689807	.1049342
65-74	.162363	.0116351	13.95	0.000	.1394231	.1853029
75+	189536	.0116863	16.22	0.000	.1664952	.2125767
/5+	1 .189536	.0116863	10.22	0.000	.1004952	.2125767
race	 					
Black	1178243	.0103882	-11.34	0.000	1383058	0973428
Hispanic	1150025	.0131188	-8.77	0.000	1408676	0891373
Asian	1407749	.0161656	-8.71	0.000	172647	1089028
Other	032871	.0346938	-0.95	0.345	1012734	.0355313
Other	032071	.0346936	-0.95	0.343	1012/34	.0333313
fpl						
Poor	0565723	.0134472	-4.21	0.000	0830849	0300598
Near Poor	0510409	.0181924	-2.81	0.006	0869091	0151727
Low Income	0391438	.0113795	-3.44	0.001	0615798	0167079
Middle Income	0371092	.0098996	-3.75	0.000	0566273	0175912
Middle income	0371092	.0090990	-3.75	0.000	0300273	01/3912
education						
Grade 8 and below	.0024143	.0155315	0.16	0.877	0282076	.0330363
Some High School	0162994	.0117257	-1.39	0.166	0394178	.006819
Some College	.0488912	.0096691	5.06	0.000	.0298276	.0679547
College	.0901982	.0099331	9.08	0.000	.0706141	.1097823
Advanced Degree	.103468	.0126997	8.15	0.000	.0784293	.1285068
notmsa	0135874	.0088065	-1.54	0.124	0309502	.0037754
region						
Midwest	.0003883	.0115426	0.03	0.973	0223691	.0231458
South	0122769	.0100813	-1.22	0.225	0321532	.0075993
West	0192716	.0110263	-1.75	0.082	041011	.0024678
cons	l .5879307	.0151007	38.93	0.000	.5581581	.6177033
					.5551561	
. eststo lpm2						

```
. * Table 3
. esttab lpm2 using hw4table3.rtf, se r2 replace keep(2.inssexcat 3.inssexcat ///
> 4.inssexcat 5.inssexcat 6.inssexcat 7.inssexcat 8.inssexcat) ///
> mtitles(LPM) coeflabels(2.inssexcat "Private Insurance - Women" 3.inssexcat "Public Insurance - Men" ///
> 4.inssexcat "Public Insurance - Women" 5.inssexcat "Uninsured - Men" 6.inssexcat "Uninsured - Women" ///
> 7.inssexcat "Medicare - Men" 8.inssexcat "Medicare - Women") ///
```

> title(TABLE 3. LPM Coefficients, Model 2)
(output written to hw4table3.rtf)

. * Logit Model

Survey: Logistic regression

[.] svy, subpop(age18over): logit obtotv08n ib1.inssexcat i.healthstatus ib3.agecat i.race $\ensuremath{///}$

> ib5.fpl ib3.education notmsa ib1.region
(running logit on estimation sample)

1		Linearized		D> 1 . 1	5050 0 6	
obtotv08n	Coef.	Std. Err.	t 	P> t	[95% Conf.	Interval]
inssexcat	 					
Priv Ins Women	.9512115	.0496533	19.16	0.000	.8533148	1.049108
Medicaid Men	.1186804	.1208557	0.98	0.327	1195992	.35696
Medicaid Women	1.149864	.1021498	11.26	0.000	.9484652	1.351263
Uninsured Men	9656823	.0859632	-11.23	0.000	-1.135168	7961969
Uninsured Women	3818811	.0843203	-4.53	0.000	5481273	215635
Medicare Men	.2383294	.1377179	1.73	0.085	0331958	.5098545
Medicare Women	.9195457	.1595805	5.76	0.000	.6049163	1.234175
healthstatus	 					
Very Good	.4127457	.0589983	7.00	0.000	.2964245	.5290669
Good	.6793008	.0666499	10.19	0.000	.5478937	.810708
Fair	1.370507	.0898606	15.25	0.000	1.193337	1.547676
Poor	2.15732	.1987641	10.85	0.000	1.765436	2.549204
agecat	 					
18-24	0595924	.0685782	-0.87	0.386	1948013	.0756165
45-64	.4947306	.0562597	8.79	0.000	.3838089	.6056524
65-74	1.23893	.1173271	10.56	0.000	1.007608	1.470253
75+	1.785625	.1639472	10.89	0.000	1.462386	2.108864
race	(044170	0506745	11 04	0 000	0101007	F7070F
Black	6944178	.0586745	-11.84 -8.66	0.000	8101007	578735
Hispanic Asian	6218349 8599299	.0717762 .0855788	-8.66 -10.05	0.000	763349 -1.028657	4803207 6912025
Other	2511919	.2096103	-10.03	0.000	6644603	.1620766
Other	2311919	.2090103	-1.20	0.232	0044003	.1020700
fpl						
Poor	36992	.0816197	-4.53	0.000	5308418	2089982
Near Poor	3545885	.1162897	-3.05	0.003	5838656	1253113
Low Income	2624286	.0725383	-3.62	0.000	4054454	1194119
Middle Income	2496556	.0621756	-4.02	0.000	3722413	12707
education	<u> </u> 					
Grade 8 and below	0393499	.1030583	-0.38	0.703	24254	.1638402
Some High School	0955722	.0679421	-1.41	0.161	229527	.0383827
Some College	.2877786	.0604707	4.76	0.000	.1685543	.4070029
College	.5670646	.0680307	8.34	0.000	.432935	.7011942
Advanced Degree	.696993	.0995001	7.00	0.000	.5008182	.8931678
notmsa	 1003801	.0593549	-1.69	0.092	2174044	.0166442
region	 					
Midwest	0095235	.0781824	-0.12	0.903	1636683	.1446212
South	0830117	.0682538	-1.22	0.225	2175811	.0515578
West	12984	.0734891	-1.77	0.079	2747315	.0150514
_cons	.2607229	.0860613	3.03	0.003	.0910441	.4304017

.

```
. eststo logit3
. * Table 4
. esttab logit3 logit3 using hw4table4.rtf, se r2 replace keep(2.inssexcat 3.inssexcat
///
> 4.inssexcat 5.inssexcat 6.inssexcat 7.inssexcat 8.inssexcat) ///
> mtitles(Coefficients OR) coeflabels(2.inssexcat "Private Insurance - Women"
3.inssexcat "Public Insurance
> - Men" ///
> 4.inssexcat "Public Insurance - Women" 5.inssexcat "Uninsured - Men" 6.inssexcat
"Uninsured - Women" ///
> 7.inssexcat "Medicare - Men" 8.inssexcat "Medicare - Women") ///
> title(TABLE 4. Logit Coefficients and Odds Ratios, Model 2) eform(0 1)
(output written to hw4table4.rtf)
. /*2g*/
. * Quietly
. svy, subpop(age18over): logit obtotv08n ib1.race ib3.agecat ib5.fpl notmsa ///
> ibl.inssexcat ib3.education ibl.region ibl.healthstatus
(running logit on estimation sample)
Survey: Logistic regression
                                                  Number of obs = 31258
Population size = 284307457
Number of strata = 165
Number of PSUs = 370
                                                    Subpop. no. of obs = 20107
                                                    Subpop. size = 207295725
Design df = 205
                                                                       = 205
= 75.83
                                                    F(32, 174) =
                                                    Prob > F
                                                                              0.0000
    ______
                            Linearized
         obtotv08n | Coef. Std. Err.
                                                   t P>|t| [95% Conf. Interval]
               race |
                       -.6944178 .0586745 -11.84 0.000 -.8101007
-.6218349 .0717762 -8.66 0.000 -.763349
            Black |
                                                                                  -.578735
                                                                      -.763349 -.4803207
          Hispanic |
            Asian | -.8599299 .0855788 -10.05 0.000 -1.028657 -.6912025
             Other | -.2511919 .2096103
                                                  -1.20 0.232 -.6644603
                                                                                    .1620766
             agecat |
             18-24 | -.0595924 .0685782 -0.87 0.386 -.1948013 .0756165
             45-64 | .4947306 .0562597
                                                  8.79 0.000 .3838089
                                                                                   .6056524
                         1.23893 .1173271 10.56 0.000 1.007608 1.470253
             65-74 |
              75+ |
                       1.785625 .1639472 10.89 0.000
                                                                     1.462386 2.108864
                fpl |

      Poor | -.36992
      .0816197
      -4.53
      0.000
      -.5308418
      -.2089982

      Near Poor | -.3545885
      .1162897
      -3.05
      0.003
      -.5838656
      -.1253113

      Low Income | -.2624286
      .0725383
      -3.62
      0.000
      -.4054454
      -.1194119

      Middle Income | -.2496556
      .0621756
      -4.02
      0.000
      -.3722413
      -.12707
```

notmsa | -.1003801 .0593549 -1.69 0.092 -.2174044 .0166442

0.98 0.327 -.1195992

.8533148 1.049108

.9512115 .0496533 19.16 0.000

Medicaid Women | 1.149864 .1021498 11.26 0.000 .9484652 1.351263 Uninsured Men | -.9656823 .0859632 -11.23 0.000 -1.135168 -.7961969 Uninsured Women | -.3818811 .0843203 -4.53 0.000 -.5481273 -.215635

inssexcat | Priv Ins Women |

Medicaid Men | .1186804 .1208557

Medicare Men	.2383294	.1377179	1.73	0.085	0331958	.5098545
Medicare Women	.9195457	.1595805	5.76	0.000	.6049163	1.234175
education						
Grade 8 and below	0393499	.1030583	-0.38	0.703	24254	.1638402
Some High School	0955722	.0679421	-1.41	0.161	229527	.0383827
Some College	.2877786	.0604707	4.76	0.000	.1685543	.4070029
College	.5670646	.0680307	8.34	0.000	.432935	.7011942
Advanced Degree	.696993	.0995001	7.00	0.000	.5008182	.8931678
navaneca begies		.0330001	,	0.000	.0000102	.0301070
region	1					
_	1 0005005	0701004	0 10	0 000	1.62.6602	1 4 4 6 0 1 0
Midwest	0095235	.0781824	-0.12	0.903	1636683	.1446212
South	0830117	.0682538	-1.22	0.225	2175811	.0515578
West	12984	.0734891	-1.77	0.079	2747315	.0150514
healthstatus						
Very Good	.4127457	.0589983	7.00	0.000	.2964245	.5290669
Good	.6793008	.0666499	10.19	0.000	.5478937	.810708
Fair	1.370507	.0898606	15.25	0.000	1.193337	1.547676
Poor	2.15732	.1987641	10.85	0.000	1.765436	2.549204
1001	1 2.13/32	.170/041	10.00	0.000	1.700400	2.549204
	1 0607000	0060613	2 02	0 000	0010441	4204017
_cons	.2607229	.0860613	3.03	0.003	.0910441	.4304017

. margins, dydx(inssexcat) noestimcheck

Average marginal effects Number of obs = 26721

Model VCE : Linearized

Expression : Pr(obtotv08n), predict()

dy/dx w.r.t. : 2.inssexcat 3.inssexcat 4.inssexcat 5.inssexcat 6.inssexcat 7.inssexcat

8.inssexcat

			Delta-method				
		dy/dx	Std. Err.	Z	P> z	[95% Conf.	<pre>Interval]</pre>
	-+-						
inssexcat							
Priv Ins Women		.1594575	.0079347	20.10	0.000	.1439058	.1750092
Medicaid Men		.0227213	.0228466	0.99	0.320	0220572	.0674998
Medicaid Women		.1852411	.0135743	13.65	0.000	.1586359	.2118464
Uninsured Men		1981353	.0178939	-11.07	0.000	2332067	1630638
Uninsured Women		076672	.0173164	-4.43	0.000	1106116	0427325
Medicare Men		.0449397	.0252596	1.78	0.075	0045683	.0944476
Medicare Women		.1550918	.0228278	6.79	0.000	.1103502	.1998334

Note: dy/dx for factor levels is the discrete change from the base level.

. est store margins

. * Table 5

(output written to hw4table5.rtf)

[.] esttab margins using hw4table5.rtf, se r2 replace keep(2.inssexcat 3.inssexcat ///

> 4.inssexcat 5.inssexcat 6.inssexcat 7.inssexcat 8.inssexcat) ///

> mtitles(Marginal Effects) coeflabels(2.inssexcat "Private Insurance - Women"

^{3.}inssexcat "Public Insurance

> - Men" ///

> 4.inssexcat "Public Insurance - Women" 5.inssexcat "Uninsured - Men" 6.inssexcat "Uninsured - Women" ///

> 7.inssexcat "Medicare - Men" 8.inssexcat "Medicare - Women") ///

> title(TABLE 5. Logit Marginal Effects, Model 2)

end of do-file
. log close
 name: <unnamed>
 log: /Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods Analysis/Answers/Assignment4_2016.lo
> g
 log type: text
 closed on: 4 Oct 2016, 15:48:43
