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

Computer Exercise #3: Estimating the Effect of Health Status, Poverty Status, and Census Region on having an Office Based Physician Visits using LPM, Logistic, and Probit Regression Models

Due: September 20, 2016

### **Answer Guide**

Use the analysis file you built in computer exercise #1. For this analysis, limit the sample to adults, i.e., persons over the age of 17.

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

1. What are the strengths and weaknesses of the linear probability model?

The main strength of the linear probability model is that the interpretation of coefficients on your independent variable are straightforward and easier to interpret as you would a usual OLS regression – that they are marginal effects of the covariates on the outcome. It has a number of weaknesses. First, predictions of the outcome variable may fall outside of one and zero, i.e., less than zero or more than one. These would be nonsensical since probabilities must fall between zero and one. Another weakness is the non-normality of errors – they are binomial. Heteroskedasticity related to the  $\beta$  is also present -  $\beta$  is inefficient and the standard errors are biased. Thus, some predictions and hypothesis tests may be biased and inaccurate. In addition, as with OLS, the marginal effects are constant unless the model is nonlinear in the parameters.

2. What is the fundamental difference between the logistic regression and probit regression models?

The main difference lies in the assumption regarding the error terms in the model. In logistic regression, the errors are assumed to follow the logistic distribution while in probit regression, the errors are assumed to follow the normal distribution. That is, the link functions, i.e., the function that relates the mean of the response to the predictors of the model, of the two are different. Graphically, the logistic function has flatter tails and the probit function approaches the axes more quickly than the curve. However, in practice the logit and the probit link functions give very similar outputs when given the same inputs. Thus, researchers sometimes use logistic and probit regression interchangeably.

3. Estimate the following model using linear probability model (LPM), logistic, and probit regression techniques.

Any obvisit = f(health status, age, race/ethnicity, sex, poverty status, education, insurance status and location) *Use the following reference categories: excellent health, age category 25-44, male, white non-Hispanic, HS diploma/GED, high income, privately insured, msa, East* 

a. Create table 1 that displays the coefficients for each model for the race/ethnicity and sex.

TABLE 1. LPM, Logit, Probit Model Coefficients

	(1)	(2)	(3)
	LPM	Logit	Probit
visit	***	***	***
Black	-0.118***	-0.690***	-0.409 <sup>***</sup>
	(0.0104)	(0.0582)	(0.0345)
Hispanic	-0.115 <sup>***</sup>	-0.620***	-0.367***
	(0.0131)	(0.0716)	(0.0423)
Asian	-0.141***	-0.853***	-0.493***
	(0.0160)	(0.0847)	(0.0500)
Other	-0.0335	-0.242	-0.144
	(0.0342)	(0.210)	(0.118)
Female	0.139***	0.863***	0.496***
	(0.00568)	(0.0374)	(0.0214)
Ν	` 31323 <sup>′</sup>	`31323 <sup>′</sup>	`31323 <sup>´</sup>
$R^2$	0.205		

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

b. Interpret the coefficients for race/ethnicity and sex from each model.

For the linear probability model, being Black, Hispanic, or Asian decreases the predicted probability of having any physician office visit by 0.118, 0.115, and 0.141 compared to being White, respectively, holding all other variables constant. These are statistically significant. The effect of belonging to other races is not statistically significant. On the other hand, being female increases the predicated probability of having any physician office visit by 0.139 compared to being male, holding all other things constant and this is also statistically significant.

For the logit model, being Black, Hispanic, or Asian decreases the log odds of having any physician office visit by 0.69, 0.62, and 0.853 compared to being White, respectively, holding all other variables constant. These are statistically significant. The effect of belonging to other races is also not statistically

significant. On the other hand, being female increases the log odds of having any physician office visit by 0.863 compared to being male and this is also statistically significant.

For the probit model, being Black, Hispanic, or Asian, the probability of having any physician office visit is associated with having a change in predicted z-score of -0.409, -0.367, and -0.493 compared to being White, holding all other things constant. These are all statistically significant. The effect of belonging to other races is also not statistically significant. On the other hand, for females, the probability of having any physician office visit is associated with having a predicted z-score of 0.869 compared to being male. This is also statistically significant.

c. Compute and display in table 2 the odds ratios from the logistic regression model for race/ethnicity and sex. Interpret the odds ratios.

TABLE 2. Logistic Regression Odds Ratios

I ABLE 2. Logistic Regression Odds Ratios.					
,	(1) Odds Ratio				
visit Black	0.502*** (0.0292)				
Hispanic	0.538 <sup>***</sup> (0.0385)				
Asian	0.426*** (0.0361)				
Other Race	0.785 (0.165)				
Female	2.371*** (0.0887)				
N	31323				

Exponentiated coefficients; Standard errors in parentheses p < 0.05, p < 0.01, p < 0.001

For Blacks, the odds of having any physician office visits is 0.502 times that of the odds for Whites. For Hispanics, the odds of having any physician office visits is 0.538 times that of the odds for Whites. For Asians, the odds of having any physician office visits is 0.426 times that of the odds for Whites. These are all statistically significant. The odds ratio for other races is not found to be statistically significant.

The odds of women having any physician office visits is 2.37 times the odds of men having any physician office visits. This is found to be statistically significant.

d. Compute and display in table 3 the marginal effects for race/ethnicity and sex from the probit and logistic regression models using the margin command in Stata? Interpret the marginal effects.

TABLE 3. Logistic and Probit Marginal Effects.

	r robit marginal Enocio.	1-1
	(1)	(2)
	Logit, Marginal Effects	Probit, Marginal Effects
Black	-0.121 <sup>***</sup>	-0.122 <sup>***</sup>
	(0.0106)	(0.0107)
Hispanic	-0.108***	-0.108***
	(0.0130)	(0.0131)
		,
Asian	-0.152 <sup>***</sup>	-0.149 <sup>***</sup>
	(0.0161)	(0.0161)
Other Race	-0.0399	-0.0406
Other Nace	(0.0358)	(0.0342)
	(0.0336)	(0.0342)
Female	0.146***	0.143***
	(0.00619)	(0.00607)
N	`26790 <i>´</i>	` 26790 ´

Marginal effects; Standard errors in parentheses (d) for discrete change of dummy variable from 0 to 1 p < 0.05, p < 0.01, p < 0.01

We first interpret the logit model marginal effects. Relative to white individuals, black, Hispanic, and Asian individuals have 0.121, 0.108, and 0.152 lower probabilities of having any office-based provider visit. These have been found to be statistically significant. In addition, compared to males, females have a 0.146 higher probability of having any office-based provider visit.

We next interpret the probit model marginal effects. Relative to white individuals, black, Hispanic, and Asian individuals have 0.122, 0.108, and 0.149 lower probabilities of having any office-based provider visit. These have been found to be statistically significant. In addition, compared to males, females have a 0.143 higher probability of having any office-based provider visit.

4. Predict the dependent variable using all three techniques. Compute the mean, standard deviations, minimum and maximum values the actual and predicted dependent variables. Display your results in table 4. Discuss how and why they are similar and/or different.

We see that the predicted means for the LPM, logit, and probit models are quite similar to the actual mean from our data. However, we see that the standard deviation for the actual data is much higher than those computed for the three models. This may be due to the fact that the actual data only contains 0s and 1s while the three models have predicted values in the (0,1) interval since represent latent probabilities. We also

note that the maximum predicted value in the LPM is 1.268, which is greater than one and does not make sense in the context of our analysis. This represents one of the weaknesses of the LPM that was discussed in number 1.

TABLE 4. Actual and Predicted Values.

Variable	Mean	SD	Min	Max	
Actual	0.667	0.471	0.000	1.000	
Linear	0.657	0.202	0.104	1.268	
Logit	0.652	0.220	0.097	0.997	
Probit	0.652	0.216	0.093	0.999	

#### Do-file

\* September 20, 2016

\* Advanced methods in health services research: analysis - 309.716

```
* Assignment # 3: Suggested code
set varabbrev off
log using "/Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods -
Analysis/Answers/Assignment3_2016.log", replace
use "/Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/meps08.dta"
cd "/Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/Answers"
svyset varpsu [pweight = perwt08f], strata(varstr)
** Data preparation
* Trimming/cleaning the data
summ totexp08
summ totexp08, detail
gen healthexp = totexp08
replace healthexp = . if totexp08 < 0 /*replaces negative values with missing*/
replace healthexp = . if totexp08 > 100000 /*replaces values > $100,000 with missing*/
summ healthexp
summ healthexp, detail
gen income = ttlp08x
replace income = . if ttlp08x < 0 /*sets negative values to missing*/
replace income = . if ttlp08x > 170000 /*sets very large values to missing*/
/* Note: If you did not exclude those with incomes > 170000, it's fine*/
summarize income
summarize income, detail
* Generate categories
summarize age08x
gen age = age08x
replace age = . if age08x < 0 /*sets negative values to missing*/
summarize age
gen agecat = 1 if age08x >=0 & age08x <=24
replace agecat = 2 if age08x >=25 & age08x <=44
replace agecat = 3 if age08x >=45 & age08x <=64
replace agecat = 4 if age08x >=65 & age08x <=74
replace agecat = 5 if age08x >=75
label define agecats 1 "18-24" 2 "25-44" 3 "45-64" 4 "65-74" 5 "75+"
label values agecat agecats /*set label name sexn to the variable sex*/
gen female = 0 if sex == 1
replace female = 1 if sex == 2
label define sexn 0 "Male" 1 "Female"
label values female sexn
```

label define raceethn 1 "Hispanic" 2 "Black non-Hispanic" 3 "Asian non-Hispanic" 4 "Other race/not Hispanic"

#### label values racethnx raceethn

```
Islander" 6 "Multiple races reported"
label values racex racexn
gen race = 1 if racex == 1 & racethnx != 1
replace race = 2 if racex == 2 & racethnx != 1
replace race = 3 if racethnx == 1
replace race = 4 if racex == 4 & racethnx != 1
replace race = 5 if (racex == 3 | racex == 5 | racex == 6) & racethnx != 1
label define racexn2 1 "White" 2 "Black" 3 "Hispanic" 4 "Asian" 5 "Other"
label values race racexn2
gen education = 1 if educyr >= 0 & educyr <= 8
replace education = 2 if educyr >= 9 & educyr <= 12 & hideg == 1 /* Some High School*/
replace education = 2 if educyr >= 9 & educyr <= 11 & hideg <0 /* Some High School but didn't answer hideg
question*/
replace education = 3 if hideg == 2 | hideg == 3 /*High School*/
replace education = 4 if educyr >=13 & educyr <=17 & hideg == 3 /*Some college-In school but only have high
school diploma*/
replace education = 5 if hideg == 4
replace education = 6 if hideg == 5 | hideg == 6
replace education = 6 if educyr == 17 & hideg == 7 /*Advanced Degree* - implies law degree or similar type*/
label define educn 1 "No High School" 2 "Some High" 3 "High School/GED" 4 "Some College/Tech School/AA
degree" 5 "College" 6 "Advanced Degree"
label values education educn
gen insurance = 1 if inscov08 ==1
replace insurance = 2 if inscov08 == 2 & mcrev08 == 2 /*Had public insurance but not medicare*/
replace insurance = 3 if inscov08 == 3
replace insurance = 4 if inscov08 == 2 & mcrev08 == 1 /* Medicare */
label define insr 1 "Private Insurance" 2 "Public Insurance" 3 "Uninsured" 4 "Medicare"
label values insurance insr
gen msa = 0 if msa08 == 0
replace msa = 1 if msa08 == 1
label define msan 0 "Not in MSA" 1 "In MSA"
label values msa msan
gen region = 1 if region08 == 1
replace region = 2 if region08 == 3
replace region = 3 if region08 == 2
replace region = 4 if region08 == 4
label define regi 1 "North East" 2 "South" 3 "Midwest" 4 "West"
label values region regi
gen healthstatus = 1 if rthlth42 == 1
```

label define racexn 1 "White" 2 "Black" 3 "Amer Indian/Alaska Native" 4 "Asian" 5 "Native Hawaiian/Pacific

```
replace healthstatus = 2 if rthlth42 == 2
replace healthstatus = 3 if rthlth42 == 3
replace healthstatus = 4 if rthlth42 == 4
replace healthstatus = 5 if rthlth42 == 5
label define health 1 "Excellent" 2 "Very Good" 3 "Good" 4 "Fair" 5 "Poor"
label values healthstatus health
gen fpl = 1 if povcat08 == 1
replace fpl = 2 if povcat08 == 2
replace fpl = 3 if povcat08 == 3
replace fpl = 4 if povcat08 == 4
replace fpl = 5 if povcat08 == 5
label define fplstat 1 "Poor" 2 "Near Poor" 3 "Low Income" 4 "Middle Income" 5 "High Income"
label values fpl fplstat
* Generate indicator variable for adult
gen adult = 0
replace adult = 1 if age08x > 17
* Generate indicator variable for office visit
gen visit = 0
replace visit = 1 if obtotv08 > 0
** Number 3 **
* Table 1 Construction
* Linear probability model
svy, subpop(adult): reg visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
eststo lpm
* Logit regression
svy, subpop(adult): logit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
eststo logit1
* Probit regression
svy, subpop(adult): probit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
eststo probit1
* Actual Table 1
esttab lpm logit1 probit1 using "hw3table1.rtf", se replace r2 keep(1.female 2.race 3.race 4.race 5.race) ///
mtitles(LPM Logit Probit) coeflabels(2.race Black 3.race Hispanic 4.race Asian ///
5.race Other 1.female Female) title(TABLE 1. LPM, Logit, Probit Model ///
Coefficients)
* Table 2 Construction
```

\* Logistic Regression for Odds Ratios

```
svy, subpop(adult): logistic visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education i.insurance ib1.msa ib1.region
eststo logistic1
* Actual Table 2
esttab logistic1 using "hw3table2.rtf", se replace eform keep(1.female 2.race 3.race 4.race 5.race) ///
mtitles(Odds Ratios) coeflabels(2.race Black 3.race Hispanic 4.race Asian ///
5.race "Other Race" 1.female Female) title(TABLE 2. Logistic Regression Odds Ratios.)
* Table 3 Construction
* Logit regression, marginal effects
svy, subpop(adult): logit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
margins, dydx(race female) post
est store margins1
* Probit regression
svy, subpop(adult): probit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
margins, dydx(race female) post
est store margins2
* Actual Table 3
esttab margins1 margins2 using hw3table3.rtf, se replace margin keep(1.female 2.race 3.race 4.race 5.race) ///
mtitles("Logit, Marginal Effects" "Probit, Marginal Effects") ///
coeflabels(2.race Black 3.race Hispanic 4.race Asian ///
5.race "Other Race" 1.female Female) title(TABLE 3. Logistic and Probit Marginal Effects.)
** Number 4 **
svy, subpop(adult): reg visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
predict predlpm
label var predlpm "Predicted Values - LPM"
svy, subpop(adult): logit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
predict predlogit
label var predlogit "Predicted Values - Logit"
svy, subpop(adult): probit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
predict predprobit
label var predprobit "Predicted Values - Probit"
tabstat visit predlpm predlogit predprobit, statistics(mean sd min max) col(stat) ///
format(%9.3f)
```

# Log file

```
name: <unnamed>
log: /Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods -
Analysis/Answers/Assignment3 2016.lo
> g
 log type: text
 opened on: 22 Sep 2016, 01:30:34
. use "/Users/jojo/Documents/JHU/TA Folder/Advanced HSR Methods - Analysis/meps08.dta"
. 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)
     pweight: perwt08f
        VCE: linearized
  Single unit: missing
    Strata 1: varstr
       SU 1: varpsu
       FPC 1: <zero>
. ** Data preparation
. * Trimming/cleaning 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
     0
                    0
            0
5%
10%
                           0
10% 0
25% 67
                                  Obs
                           0
                                                  33066
                                 Sum of Wgt. 33066
                         0
50% 528.5
                                               3142.069
                                  Mean
                                 Std. Dev.
                    Largest
                                                9786.619
75% 2425
90% 7453
95% 13582
99% 40763
                      238659
                     264510
373799
553493
                                               9.58e+07
14.40863
469.447
                                 Variance
                                 Skewness
Kurtosis
. 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*/(42 real changes made, 42 to missing)
. summ healthexp
  Variable | Obs Mean Std. Dev.
                                                  Min
                                                            Max
 healthexp | 33024 2937.216 7412.106 0 99988
. summ healthexp, detail
                       healthexp
   Percentiles Smallest
1% 0
5% 0
10% 0
25% 66
                    0
                           0
                                 Obs 33024
Sum of Wgt. 33024
                      0
```

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\*/
- . 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
- . summarize age08x

Variable		Obs	Mean	Std. Dev	. Min	Max
	+					
age08x	1	33066	33.69395	22.38051	-1	85

- . gen age = age08x
- . replace age = . if age08x < 0 /\*sets negative values to missing\*/ (251 real changes made, 251 to missing)
- . summarize age

Variable		Obs	Mean	Std.	Dev.	Min	Max
	+						
age	1 3	2815 33.	95932	22.25	5851	0	85

.

- . gen agecat = 1 if age08x >=0 & age08x <=24 (20062 missing values generated)
- . replace agecat = 2 if age08x >=25 & age08x <=44 (8813 real changes made)
- . replace agecat = 3 if age08x >=45 & age08x <=64  $(7614\ \text{real changes made})$
- . replace agecat = 4 if age08x >=65 & age08x <=74 (1867 real changes made)
- . replace agecat = 5 if age08x >=75 (1517 real changes made)
- . label define agecats 1 "18-24" 2 "25-44" 3 "45-64" 4 "65-74" 5 "75+"

```
. label values agecat agecats /* set label name sexn to the variable sex*/
. gen female = 0 if sex == 1
(17181 missing values generated)
. replace female = 1 if sex == 2
(17181 real changes made)
. label define sexn 0 "Male" 1 "Female"
. label values female sexn
. label define raceethn 1 "Hispanic" 2 "Black non-Hispanic" 3 "Asian non-Hispanic" 4 "Other race/not
Hispani
> c"
. label values racethnx raceethn
. label define racexn 1 "White" 2 "Black" 3 "Amer Indian/Alaska Native" 4 "Asian" 5 "Native
Hawaiian/Pacific
> Islander" 6 "Multiple races reported"
. label values racex racexn
. 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
. gen education = 1 if educyr >=0 & educyr <=8
(25465 missing values generated)
. replace education = 2 if educyr >=9 & educyr <=12 & hideg == 1 /*Some High School*/
(3732 real changes made)
. replace education = 2 if educyr >=9 & educyr <=11 & hideq <0 /* Some High School but didn't answer
hideg q
> uestion*/
(3 real changes made)
. replace education = 3 if hideg == 2 | hideg == 3 /*High School*/
(11173 real changes made)
. replace education = 4 if educyr >=13 & educyr <=17 & hideg == 3 /*Some college-In school but only
have hig
> h school diploma*/
(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)
```

```
. replace education = 6 if educyr == 17 & hideg == 7 /*Advanced Degree* - implies law degree or
similar type
(66 real changes made)
. label define educn 1 "No High School" 2 "Some High" 3 "High School/GED" 4 "Some College/Tech
School/AA deg
> ree" 5 "College" 6 "Advanced Degree"
. label values education educn
. gen insurance = 1 if inscov08 ==1
(14773 missing values generated)
. replace insurance = 2 if inscov08 == 2 & mcrev08 == 2 /*Had public insurance but not medicare*/
(6642 real changes made)
. replace insurance = 3 if inscov08 == 3
(5662 real changes made)
. replace insurance = 4 if inscov08 == 2 & mcrev08 == 1 /* Medicare */
(2469 real changes made)
. label define insr 1 "Private Insurance" 2 "Public Insurance" 3 "Uninsured" 4 "Medicare"
. label values insurance insr
. gen msa = 0 if msa08 == 0
(28406 missing values generated)
. replace msa = 1 if msa08 == 1
(28155 real changes made)
. label define msan 0 "Not in MSA" 1 "In MSA"
. label values msa msan
. gen region = 1 if region08 == 1
(28080 missing values generated)
. replace region = 2 if region08 == 3
(12424 real changes made)
. replace region = 3 if region08 == 2
(6499 real changes made)
. replace region = 4 if region08 == 4
(8906 real changes made)
. label define regi 1 "North East" 2 "South" 3 "Midwest" 4 "West"
. label values region regi
. 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 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
. * Generate indicator variable for adult
. gen adult = 0
. replace adult = 1 \text{ if age}08x > 17
(23183 real changes made)
. * Generate indicator variable for office visit
. gen visit = 0
. replace visit = 1 if obtotv08 > 0
(22054 real changes made)
. ** Number 3 **
. * Table 1 Construction
. * Linear probability model
. svy, subpop(adult): reg visit ib1.healthstatus ib2.agecat ib1.race i.female ///
> ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
(running regress on estimation sample)
Survey: Linear regression
                                                        Number of obs = 31323
Population size = 285026364
Number of strata =
                             165
Number of PSUs =
                              370
                                                        Subpop. no. of obs =
                                                                                   20172
                                                       Subpop. size = 208014633

Design df = 205

F( 29, 177) = 197.62

Prob > F = 0.0000

R-squared = 0.2046
                                                        R-squared
                                                                                     0.2046
 ______
                                  l Linearized visit | Coef. Std. Err.
                                                                           t P>|t| [95% Conf. Interval]
                          healthstatus |
                                                                                              .0521939
                             Very Good | .0728289 .0104661 6.96 0.000

Good | .1160581 .011265 10.30 0.000

Fair | .200874 .0124207 16.17 0.000

Poor | .2531628 .0153289 16.52 0.000
                                                                                                             .0934639
                                                                                              .0938479 .1382683
.1763852 .2253628
                                                                                               .2229404
                                                                                                            .2833852
                                  agecat |

    18-24
    | -.0263929
    .013486
    -1.96
    0.052

    45-64
    | .0861886
    .009213
    9.36
    0.000

    65-74
    | .1611664
    .011619
    13.87
    0.000

    75+
    | .1867627
    .0117369
    15.91
    0.000

                                  18-24 | -.0263929 .013486
45-64 | .0861886 .009213
                                                                                                              .0001961
                                                                                               -.0529819
                                                                                             -.0529819 .0001961
.0680242 .1043531
                                                                                                            .1840745
                                                                                               .1382584
                                                                                                              .2099032
```

race |

Black Hispanic Asian Other	1179558 1153449 1405633 0334904	.0103721 .0130775 .0160152 .034236	-11.37 -8.82 -8.78 -0.98	0.000 0.000 0.000 0.329	1384055 1411285 1721389 1009902	0975061 0895613 1089877 .0340095
female Female	   .1391388 	.0056773	24.51	0.000	.1279454	.1503323
fpl Poor Near Poor Low Income Middle Income	055755 0515948 0387547 0357165	.0133805 .0181077 .0113305 .0098132	-4.17 -2.85 -3.42 -3.64	0.000 0.005 0.001 0.000	082136 0872961 0610939 0550642	0293741 0158935 0164154 0163687
education No High School Some High Some College/Tech School/AA degree College Advanced Degree	.0020783 0168397 .0492705 .0908042 .1032375	.0155323 .0116099 .0096024 .0099263 .0123633	0.13 -1.45 5.13 9.15 8.35	0.894 0.148 0.000 0.000	0285451 0397299 .0303384 .0712334 .078862	.0327017 .0060506 .0682027 .1103749 .127613
insurance Public Insurance Uninsured Medicare msa	.0352607	.0151494 .0142871 .0107681	2.33 -17.20 1.88	0.021 0.000 0.061	.005392 2739193 0009611	.0651294 2175822 .0414998
Not in MSA	0133504	.0088506	-1.51	0.133	0308002	.0040993
region South Midwest West	0116128  0116128   .0012734  0190342	.0100957 .0115397 .0110501	-1.15 0.11 -1.72	0.251 0.912 0.086	0315174 0214783 0408206	.0082918 .0240251 .0027523
_cons	.5914321	.0151045	39.16	0.000	.561652	.6212122

. eststo lpm

. \* Logit regression

. svy, subpop(adult): logit visit ib1.healthstatus ib2.agecat ib1.race i.female ///

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

Survey: Logistic regression

Number of strata = 165 Number of PSUs = 370

Number of obs = 31323 Population size = 285026364 Number of obs Subpop. no. of obs = 20172Subpop. size = 208014633 Design df = F( 29, 177) = Prob > F = = 205 = 87.36 0.0000

visit	Coef.	Linearized Std. Err.	t	P> t	[95% Conf.	Interval
healthstatus						
Very Good	.4044001	.0585686	6.90	0.000	.2889261	.5198742
Good	.6753597	.0662026	10.20	0.000	.5448345	.8058849
Fair	1.357334	.0905371	14.99	0.000	1.17883	1.535837
Poor	2.158895	.1990341	10.85	0.000	1.766478	2.551311
agecat						
18-24	0625399	.0684019	-0.91	0.362	1974014	.0723216
45-64	.48659	.0567706	8.57	0.000	.3746609	.5985191
65-74	1.227756	.1165171	10.54	0.000	.9980307	1.457482
75+	1.777876	.1636173	10.87	0.000	1.455288	2.100465
race						
Black	6897863	.0581504	-11.86	0.000	8044358	5751368
Hispanic	6199646	.0715948	-8.66	0.000	7611211	4788081
Asian	8531756	.0846568	-10.08	0.000	-1.020085	6862659

Other	2422756	.2097223	-1.16	0.249	6557649	.1712137
female		0074060	02.06	0.000	7002245	0260520
Female	.8631438	.0374362	23.06	0.000	.7893345	.9369532
fpl	 					
Poor	3689489	.0817402	-4.51	0.000	5301081	2077897
Near Poor	3572039	.1167581	-3.06	0.003	5874046	1270032
Low Income	2590297	.0720621	-3.59	0.000	4011076	1169517
Middle Income	2400863	.0615636	-3.90	0.000	3614654	1187073
education	 					
No High School	   <b></b> 0462999	.1027464	-0.45	0.653	2488751	.1562753
Some High	0955991	.0674459	-1.42	0.158	2285757	.0373774
Some College/Tech School/AA degree	.2893854	.0602219	4.81	0.000	.1706516	.4081192
College	.5677377	.0680977	8.34	0.000	.433476	.7019995
Advanced Degree	.6817271	.096589	7.06	0.000	.491292	.8721623
Advanced Degree	.0017271	.000000	7.00	0.000	. 431232	.0721025
insurance	i İ					
Public Insurance	.1882728	.0906489	2.08	0.039	.0095492	.3669964
Uninsured	-1.122397	.0706839	-15.88	0.000	-1.261757	9830359
Medicare	.1359043	.1235898	1.10	0.273	1077657	.3795743
	I					
msa						
Not in MSA	1005684	.0593348	-1.69	0.092	2175531	.0164164
region	 					
South	0840724	.0681831	-1.23	0.219	2185023	.0503576
Midwest	00681	.0780753	-0.09	0.931	1607434	.1471235
West	1300268	.0734128	-1.77	0.078	2747677	.0147142
		0005000	0.40	0 005	40640	
_cons	.2967943	.0865633	3.43	0.001	.1261259	.4674628

<sup>.</sup> eststo logit1

- . svy, subpop(adult): probit visit ib1.healthstatus ib2.agecat ib1.race i.female /// > ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
- (running probit on estimation sample)

## Survey: Probit regression

Number of strata = 165Number of PSUs = 370Number of obs = 31323 Population size = 285026364 Subpop. no. of obs = 20172 Subpop. size = 208014633 Design df = 205 F( 29, 177) = 100.41 Prob > F = 0.0000

I		Linearized				
visit	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
healthstatus						
Very Good	.2403186	.0346734	6.93	0.000	.1719564	.3086807
Good	.3924217	.0390688	10.04	0.000	.3153935	.46945
Fair	.7827303	.0526081	14.88	0.000	.679008	.8864526
Poor	1.181061	.1045621	11.30	0.000	.9749059	1.387216
agecat						
18-24	0445412	.0408581	-1.09	0.277	1250972	.0360148
45-64	.2807088	.0328794	8.54	0.000	.2158836	.3455341
65-74	.68546	.0626452	10.94	0.000	.5619485	.8089715
75+	.9440751	.0821075	11.50	0.000	.7821918	1.105959
race						
Black	4088744	.0344914	-11.85	0.000	4768778	340871
Hispanic	3674273	.0422758	-8.69	0.000	4507784	2840762
Asian	4925948	.0500003	-9.85	0.000	5911755	3940141
Other	144393	.1177109	-1.23	0.221	3764722	.0876862
Office	.144333	. 1 1 / 1 1 0 9	1.20	0.221	.5/04/22	.0070002
F1- I						
female						

<sup>. \*</sup> Probit regression

```
Female | .4964984 .0213784 23.22 0.000
                                                                                .4543486 .5386482
                                fpl |
                        -.3116526 -.1255689
                                                                                -.3414214
                                                                                            -.075182
                                                                                -.2339042
                                                                                            -.0712991
                     Middle Income | -.1393628
                                                                                -.2099246
                                                                                            -.0688009
                          education |
                    .0894446
.0149416
                                                                                            .2377621
Some College/Tech School/AA degree | .1685094 .035125
College | .3302053 .0390494
Advanced Degree | .3824849 .0541269
                                                                                             .4071953
                                                                                            .4892017
                          insurance |
                                                                                .0137013 .2245826
-.7600488 -.5960971
                  Public Insurance | .1191419 .0534797 2.23 0.027 .0137013

Uninsured | -.678073 .0415783 -16.31 0.000 -.7600488

Medicare | .0674487 .0665375 1.01 0.312 -.0637369
                          Medicare | .0674487 .0665375
                                                                                            .1986344
                                msa |
                        Not in MSA | -.0603327 .0353654 -1.71 0.090
                                                                                -.1300592
                                                                                             .0093938
                             region |
                           South | -.0473932 .040414 -1.17 0.242
Midwest | -.0035991 .0461239 -0.08 0.938
West | -.0790752 .0428784 -1.84 0.067
                                                                                           .0322872
                                                                                -.1270736
                                                                                -.0945372
                                                                                -.1636144
                                                                                             .0054639
 _cons | .2014991 .0506248
                                                               3.98 0.000
                                                                                  .101687 .3013112
. eststo probit1
```

```
. * Actual Table 1
```

(output written to hw3table1.rtf)

(running logistic on estimation sample)

Survey: Logistic regression

Number	of	strata	=	165	Number of obs	=	31323
Number	of	PSUs	=	370	Population size	=	285026364
					Subpop. no. of obs	=	20172
					Subpop. size	=	208014633
					Design df	=	205
					F( 29, 177)	=	87.36
					Prob > F	=	0.0000

visit	   Odds Ratio	Linearized Std. Err.	t	P> t	[95% Conf.	Interval]
healthstatus	+ 					
Very Good	1.498403	.0877594	6.90	0.000	1.334993	1.681816
Good	1.96474	.1300708	10.20	0.000	1.724323	2.238677
Fair	3.885818	.3518107	14.99	0.000	3.25057	4.645211
Poor	8.661558	1.723945	10.85	0.000	5.850214	12.8239
agecat						
18-24	.9393756	.0642551	-0.91	0.362	.820861	1.075001
45-64	1.626759	.0923521	8.57	0.000	1.454498	1.819422
65-74	3.413561	.3977382	10.54	0.000	2.712934	4.295129
75+	5.917277	.9681689	10.87	0.000	4.285717	8.169967

<sup>.</sup> esttab lpm logit1 probit1 using "hw3table1.rtf", se replace r2 keep(1.female 2.race 3.race 4.race

<sup>&</sup>gt; ///

<sup>&</sup>gt; mtitles(LPM Logit Probit) coeflabels(2.race Black 3.race Hispanic 4.race Asian ///

<sup>&</sup>gt; 5.race Other 1.female Female) title(TABLE 1. LPM, Logit, Probit Model ///

<sup>&</sup>gt; Coefficients)

<sup>. \*</sup> Table 2 Construction

<sup>. \*</sup> Logistic Regression for Odds Ratios

<sup>.</sup> svy, subpop(adult): logistic visit ib1.healthstatus ib2.agecat ib1.race i.female ///

<sup>&</sup>gt; ib5.fpl ib3.education i.insurance ib1.msa ib1.region

```
race |
                                    Black |
                                                 .5016833 .0291731 -11.86 0.000
.5379635 .0385154 -8.66 0.000
.4260598 .0360689 -10.08 0.000
                                                                                                     .4473403 .5626279
                                 Hispanic |
Asian |
                                                                                                      .4671424
                                                                                                                    .6195214
                                                                                                       .3605642
                                                                                                                       .5034525
                                                 .7848398 .1645984 -1.16 0.249
                                    Other |
                                                                                                       .5190449
                                                                                                                    1.186744
                                    female I
                                   Female | 2.370602 .0887463
                                                                              23.06 0.000
                                                                                                      2.201931
                                                                                                                    2.552193
                                                 .6914607 .0565201 -4.51 0.000
.6996298 .0816874 -3.06 0.003
.7718001 .0556176 -3.59 0.000
.78656 .0484235 -3.90 0.000
                                     Poor | .6914607
                                                                                                       .5885413
                                                                                                                      .8123778
                              Near Poor |
Low Income |
                                                                                                      .5557679
                                                                                                                     .8807308
                                                                                                     .669578
.6966547
                                                                                                                    .8896281
.8880677
                          Middle Income |
                                 education |
No High School | .9547556 .0980977 -0.45 0.653
Some High | .9088283 .0612967 -1.42 0.158
Some College/Tech School/AA degree | 1.335606 .0804328 4.81 0.000
College | 1.764271 .1201429 8.34 0.000
Advanced Degree | 1.97729 .1909844 7.06 0.000
                                                                                                      .7796773
                                                                                                                    1.169148
                                                                                                                    1.038085
                                                                                                       .7956661
                                                                                                      1.186077
                                                                                                                      1.503986
                                                                                                                    2.017783
2.392078
                                                                                                       1.54261
                                                                                                       1.634427
                                 insurance |
                       Public Insurance | 1.207163
Uninsured | .3254988

    1.207163
    .1094279
    2.08
    0.039

    .3254988
    .0230075
    -15.88
    0.000

    1.145572
    .141581
    1.10
    0.273

                                                                                                      1.009595
                                                                                                                     1.443393
                                                                                                       .283156
                                                                                                                      .3741734
                                                                                                                    1.461662
                                 Medicare | 1.145572
                                                                                                       .8978379
                              Not in MSA |
                                                                               -1.69 0.092
                                                  .9043233
                                                                 .0536579
                                                                                                       .8044849
                                                                                                                    1.016552
                                    region |

    South
    |
    .9193647
    .0626851
    -1.23
    0.219

    Midwest
    |
    .9932132
    .0775454
    -0.09
    0.931

    West
    |
    .8780719
    .0644617
    -1.77
    0.078

                                                                                                       .8037216
                                                                                                                    1.051647
                                                                                                      .8515105 1.158497
                                                                                                                    1.014823
                                                                                                      .7597486
                                      cons | 1.345539 .1164742 3.43 0.001
                                                                                                     1.134425 1.59594
. eststo logistic1
. * Actual Table 2
. esttab logistic1 using "hw3table2.rtf", se replace eform keep(1.female 2.race 3.race 4.race 5.race)
> mtitles(Odds Ratios) coeflabels(2.race Black 3.race Hispanic 4.race Asian ///
> 5.race "Other Race" 1.female Female) title(TABLE 2. Logistic Regression Odds Ratios.)
(output written to hw3table2.rtf)
. * Table 3 Construction
. * Logit regression, marginal effects
. svy, subpop(adult): logit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
> ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
(running logit on estimation sample)
Survey: Logistic regression
                                165
                                                           Number of obs = 31323
Population size = 285026364
Number of strata =
Number of PSUs
                                  370
                                                           Subpop. no. of obs =
                                                                                        20172
                                                           Subpop. size = 208014633
                                                                                        205
                                                           Design df
                                                           F(29, 177) = 87.36

Prob > F = 0.0000
```

visit	Coef.	Linearized Std. Err.	t	P> t	[95% Conf.	Interval]
healthstatus   Very Good	.4044001	.0585686	6.90	0.000	.2889261	.5198742
Good   Fair   Poor	.6753597 1.357334 2.158895	.0662026 .0905371 .1990341	10.20 14.99 10.85	0.000 0.000 0.000	.5448345 1.17883 1.766478	.8058849 1.535837 2.551311

	l					
agecat						
18-24	0625399	.0684019	-0.91	0.362	1974014	.0723216
45-64	.48659	.0567706	8.57	0.000	.3746609	.5985191
65-74	1.227756	.1165171	10.54	0.000	.9980307	1.457482
75+	1.777876	.1636173	10.87	0.000	1.455288	2.100465
race						
Black	6897863	.0581504	-11.86	0.000	8044358	5751368
Hispanic	6199646	.0715948	-8.66	0.000	7611211	4788081
Asian	8531756	.0846568	-10.08	0.000	-1.020085	6862659
Other	2422756	.2097223	-1.16	0.249	6557649	.1712137
female		0054060	00.00		5000045	0060500
Female	.8631438	.0374362	23.06	0.000	.7893345	.9369532
fpl						
Poor	ı  3689489	.0817402	-4.51	0.000	5301081	2077897
Near Poor	3572039	.1167581	-3.06	0.003	5874046	1270032
Low Income	2590297	.0720621	-3.59	0.000	4011076	1169517
Middle Income	2400863	.0615636	-3.90	0.000	3614654	1187073
FIGURE THEOME	1 .2400003	.0013030	3.90	0.000	.5014054	.1107075
education						
No High School	0462999	.1027464	-0.45	0.653	2488751	.1562753
Some High	0955991	.0674459	-1.42	0.158	2285757	.0373774
Some College/Tech School/AA degree	.2893854	.0602219	4.81	0.000	.1706516	.4081192
College	.5677377	.0680977	8.34	0.000	.433476	.7019995
Advanced Degree	.6817271	.096589	7.06	0.000	.491292	.8721623
insurance						
Public Insurance	.1882728	.0906489	2.08	0.039	.0095492	.3669964
Uninsured	-1.122397	.0706839	-15.88	0.000	-1.261757	9830359
Medicare	.1359043	.1235898	1.10	0.273	1077657	.3795743
msa						
Not in MSA	1005684	.0593348	-1.69	0.092	2175531	.0164164
mand an						
region South	   <b></b> 0840724	.0681831	-1.23	0.219	2185023	.0503576
Midwest	0040724	.0780753	-0.09	0.219	1607434	.1471235
Midwest	1300268	.0734128	-0.09	0.931	1607434	.14/1235
west	13UUZ08	.0/34128	-1.//	0.078	2/4/0//	.014/142
cons	.2967943	.0865633	3.43	0.001	.1261259	.4674628
					.1201233	. 107 1020

. margins, dydx(race female) post

Average marginal effects Number of obs = 26790

Model VCE : Linearized

Expression : Pr(visit), predict()
dy/dx w.r.t. : 2.race 3.race 4.race 5.race 1.female

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf.	Interval]
race						
Black	1206578	.0106126	-11.37	0.000	141458	0998576
Hispanic	1075431	.0130433	-8.25	0.000	1331075	0819787
Asian	15191	.0161397	-9.41	0.000	1835431	1202768
Other	0398655	.0357731	-1.11	0.265	1099795	.0302484
female   Female	.1461475	.0061908	23.61	0.000	.1340137	.1582813

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

<sup>.</sup> est store margins1

<sup>. \*</sup> Probit regression

<sup>.</sup> svy, subpop(adult): probit visit ibl.healthstatus ib2.agecat ib1.race i.female ///

<sup>&</sup>gt; ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region

<sup>(</sup>running probit on estimation sample)

Survey: Probit regression

Linearized Coef. Std. Err. visit | t P>|t| [95% Conf. Interval] healthstatus | .3086807 

 Very Good | .2403186
 .0346734
 6.93
 0.000
 .1719564
 .3086807

 Good | .3924217
 .0390688
 10.04
 0.000
 .3153935
 .46945

 Fair | .7827303
 .0526081
 14.88
 0.000
 .679008
 .8864526

 Poor | 1.181061
 .1045621
 11.30
 0.000
 .9749059
 1.387216

 agecat | 
 18-24
 | -.0445412
 .0408581
 -1.09
 0.277
 -.1250972
 .0360148

 45-64
 | .2807088
 .0328794
 8.54
 0.000
 .2158836
 .3455341

 65-74
 | .68546
 .0626452
 10.94
 0.000
 .5619485
 .8089715

 75+
 | .9440751
 .0821075
 11.50
 0.000
 .7821918
 1.105959
 .0360148 race | Black | -.4088744 .0344914 -11.85 0.000 -.4768778 -.340871 Hispanic | -.3674273 .0422758 -8.69 0.000 -.4507784 -.2840762 Asian | -.4925948 .0500003 -9.85 0.000 -.5911755 -.3940141 Other | -.144393 .1177109 -1.23 0.221 -.3764722 .0876862 female | Female | .4964984 .0213784 23.22 0.000 .4543486 .5386482 fpl | -.1255689 -.3116526 -.3414214 -.075182 -.2339042 -.0712991 -.2099246 -.0688009 education | insurance | Public Insurance | .0137013 .2245826 -.7600488 -.5960971 -.0637369 .1986344 msa Not in MSA | -.0603327 .0353654 -1.71 0.090 -.1300592 .0093938 region | South | -.0473932 .040414 -1.17 0.242 -.1270736 .0322872 \_cons | .2014991 .0506248 3.98 0.000 .101687 .3013112 \_\_\_\_\_

Average marginal effects Number of obs = 26790

Model VCE : Linearized

Expression : Pr(visit), predict()

dy/dx w.r.t. : 2.race 3.race 4.race 5.race 1.female

| Delta-method

<sup>.</sup> margins, dydx(race female) post

```
| dy/dx Std. Err. z P>|z| [95% Conf. Interval]
       race |
Black | -.1216121 .0106677 -11.40 0.000 -.1425203 -.1007039

Hispanic | -.1084496 .0130572 -8.31 0.000 -.1340412 -.082858

Asian | -.1486131 .0161213 -9.22 0.000 -.1802103 -.1170159

Other | -.0406136 .0342184 -1.19 0.235 -.1076805 .0264533
   female |
 Female | .1431522 .0060689 23.59 0.000 .1312574 .1550471
```

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

. est store margins2

. \* Actual Table 3

. esttab margins1 margins2 using hw3table3.rtf, se replace margin keep(1.female 2.race 3.race 4.race 5.race)

> mtitles("Logit, Marginal Effects" "Probit, Marginal Effects") ///

> coeflabels(2.race Black 3.race Hispanic 4.race Asian ///

> 5.race "Other Race" 1.female Female) title(TABLE 3. Logistic and Probit Marginal Effects.) (output written to hw3table3.rtf)

. \*\* Number 4 \*\*

. svy, subpop(adult): reg visit ib1.healthstatus ib2.agecat ib1.race i.female ///

> ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region

(running regress on estimation sample)

Survey: Linear regression

Number of strata = 165Number of PSUs = 370Number of obs = 31323 Population size = 285026364 Subpop. no. of obs = 20172 Subpop. size = 208014633 Design df 205

Design df - 197.62 F( 29, 177) = 197.62 Prob > F = 0.0000 R-squared = 0.2046

		Linearized				
visit	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
healthstatus						
Very Good	.0728289	.0104661	6.96	0.000	.0521939	.0934639
Good	.1160581	.011265	10.30	0.000	.0938479	.1382683
Fair	.200874	.0124207	16.17	0.000	.1763852	.2253628
Poor	.2531628	.0153289	16.52	0.000	.2229404	.2833852
. !						
agecat	0062000	012406	1 00	0.050	0500010	0001061
18-24	0263929	.013486	-1.96	0.052	0529819	.0001961
45-64	.0861886	.009213	9.36	0.000	.0680242	.1043531
65-74	.1611664	.011619	13.87	0.000	.1382584	.1840745
75+	.1867627	.0117369	15.91	0.000	.1636221	.2099032
race						
Black	1179558	.0103721	-11.37	0.000	1384055	0975061
Hispanic	1153449	.0130775	-8.82	0.000	1411285	0895613
Asian	1405633	.0160152	-8.78	0.000	1721389	1089877
Other	0334904	.034236	-0.98	0.329	1009902	.0340095
 female						
Female	.1391388	.0056773	24.51	0.000	.1279454	.1503323
   fpl						
Poor	055755	.0133805	-4.17	0.000	082136	0293741
Near Poor	0515948	.0133603	-2.85	0.005	0872961	0158935
Low Income	0313946	.0101077	-3.42	0.003	0610939	0164154
Middle Income	0357165	.0098132	-3.42	0.001	0550642	0163687
Middle income	033/163	.0090132	-3.04	0.000	0550642	0103007
education						
No High School	.0020783	.0155323	0.13	0.894	0285451	.0327017
Some High	0168397	.0116099	-1.45	0.148	0397299	.0060506

Some College/Tech School/AA degree   College   Advanced Degree	.0492705 .0908042 .1032375	.0096024 .0099263 .0123633	5.13 9.15 8.35	0.000 0.000 0.000	.0303384 .0712334 .078862	.0682027 .1103749 .127613
insurance						
Public Insurance	.0352607	.0151494	2.33	0.021	.005392	.0651294
Uninsured	2457508	.0142871	-17.20	0.000	2739193	2175822
Medicare	.0202693	.0107681	1.88	0.061	0009611	.0414998
msa						
Not in MSA	0133504	.0088506	-1.51	0.133	0308002	.0040993
region						
South	0116128	.0100957	-1.15	0.251	0315174	.0082918
Midwest	.0012734	.0115397	0.11	0.912	0214783	.0240251
West	0190342	.0110501	-1.72	0.086	0408206	.0027523
i						
_cons	.5914321	.0151045	39.16	0.000	.561652	.6212122

. predict predlpm
(option xb assumed; fitted values)
(6276 missing values generated)

. label var predlpm "Predicted Values - LPM"

. . svy, subpop(adult): logit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
> ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
(running logit on estimation sample)

Survey: Logistic regression

Number of strata = 165Number of PSUs = 370 Number of obs = 31323
Population size = 285026364
Subpop. no. of obs = 20172
Subpop. size = 208014633
Design df = 205
F( 29, 177) = 87.36
Prob > F = 0.0000

		Linearized				
visit	Coef.		t	P> t	[95% Conf.	<pre>Interval]</pre>
h - 1+h - + - +	·					
healthstatus	4044001	0505606	6 00	0.000	2000261	F100740
Very Good	.4044001	.0585686	6.90		.2889261	.5198742
Good	.6753597	.0662026	10.20	0.000	.5448345	.8058849
Fair	1.357334	.0905371	14.99	0.000	1.17883	1.535837
Poor	2.158895	.1990341	10.85	0.000	1.766478	2.551311
agecat						
18-24	0625399	.0684019	-0.91	0.362	1974014	.0723216
45-64	.48659	.0567706	8.57	0.000	.3746609	.5985191
65-74	1.227756	.1165171	10.54	0.000	.9980307	1.457482
75+	1.777876	.1636173	10.87	0.000	1.455288	2.100465
race						
Black	6897863	.0581504	-11.86	0.000	8044358	5751368
	6199646	.0715948	-8.66	0.000	7611211	4788081
Hispanic   Asian	8531756	.0846568	-8.66	0.000	-1.020085	4788081
Asian Other	8531756	.2097223	-10.08	0.000	-1.020085	.1712137
Other	2422736	.2097223	-1.10	0.249	6557649	.1/1213/
female						
Female	.8631438	.0374362	23.06	0.000	.7893345	.9369532
fpl						
Poor	3689489	.0817402	-4.51	0.000	5301081	2077897
Near Poor	3572039	.1167581	-3.06	0.003	5874046	1270032
Low Income	2590297	.0720621	-3.59	0.000	4011076	1169517
Middle Income	2400863	.0615636	-3.90	0.000	3614654	1187073
Middle income	2400003	.0013636	-3.90	0.000	3614634	110/0/3
education						
No High School	0462999	.1027464	-0.45	0.653	2488751	.1562753
Some High	0955991	.0674459	-1.42	0.158	2285757	.0373774
	.2893854	.0602219	4.81	0.000	.1706516	.4081192
			–			

College	.5677377	.0680977	8.34	0.000	.433476	.7019995
Advanced Degree	.6817271	.096589	7.06	0.000	.491292	.8721623
insurance						
Public Insurance	.1882728	.0906489	2.08	0.039	.0095492	.3669964
Uninsured	-1.122397	.0706839	-15.88	0.000	-1.261757	9830359
Medicare	.1359043	.1235898	1.10	0.273	1077657	.3795743
msa						
Not in MSA	1005684	.0593348	-1.69	0.092	2175531	.0164164
region						
South	0840724	.0681831	-1.23	0.219	2185023	.0503576
Midwest	00681	.0780753	-0.09	0.931	1607434	.1471235
West	1300268	.0734128	-1.77	0.078	2747677	.0147142
_cons	.2967943	.0865633	3.43	0.001	.1261259	.4674628

. predict predlogit
(option pr assumed; Pr(visit))
(6276 missing values generated)

. label var predlogit "Predicted Values - Logit"

. . svy, subpop(adult): probit visit ib1.healthstatus ib2.agecat ib1.race i.female ///
> ib5.fpl ib3.education ib1.insurance ib1.msa ib1.region
(running probit on estimation sample)

Survey: Probit regression

Number of strata = 165 Number of PSUs = 370 

 Number of obs
 =
 31323

 Population size
 =
 285026364

 Subpop. no. of obs
 =
 20172

 Subpop. size
 =
 208014633

 Design df
 =
 205

 F(29, 177)
 =
 100.41

 Prob > F
 =
 0.0000

		Linearized				
visit	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
healthstatus						
Very Good	.2403186	.0346734	6.93	0.000	.1719564	.3086807
Good	.3924217	.0390688	10.04	0.000	.3153935	.46945
Fair	.7827303	.0526081	14.88	0.000	.679008	.8864526
Poor	1.181061	.1045621	11.30	0.000	.9749059	1.387216
   agecat						
18-24	0445412	.0408581	-1.09	0.277	1250972	.0360148
45-64	.2807088	.0328794	8.54	0.000	.2158836	.3455341
65-74	.68546	.0626452	10.94	0.000	.5619485	.8089715
75+	.9440751	.0821075	11.50	0.000	.7821918	1.105959
race						
Black	4088744	.0344914	-11.85	0.000	4768778	340871
Hispanic	3674273	.0422758	-8.69	0.000	4507784	2840762
Asian	4925948	.0500003	-9.85	0.000	5911755	3940141
Other	144393	.1177109	-1.23	0.221	3764722	.0876862
Other	144393	.11//109	-1.25	0.221	3/04/22	.0070002
female						
Female	.4964984	.0213784	23.22	0.000	.4543486	.5386482
   fpl						
Poor	2186107	.047191	-4.63	0.000	3116526	1255689
Near Poor	2083017	.0675185	-3.09	0.002	3414214	075182
Low Income	1526016	.0412368	-3.70	0.000	2339042	0712991
Middle Income	1393628	.0357891	-3.89	0.000	2099246	0688009
education						
No High School	0281533	.0596458	-0.47	0.637	1457511	.0894446
Some High	0632671	.0396675	-1.59	0.112	1414757	.0149416
Some College/Tech School/AA degree	.1685094	.035125	4.80	0.000	.0992568	.2377621
College	.3302053	.0390494	8.46	0.000	.2532153	.4071953

Advanced Degree	.3824849	.0541269	7.07	0.000	.2757681	.4892017
insurance						
Public Insurance	.1191419	.0534797	2.23	0.027	.0137013	.2245826
Uninsured	678073	.0415783	-16.31	0.000	7600488	5960971
Medicare	.0674487	.0665375	1.01	0.312	0637369	.1986344
I						
msa						
Not in MSA	0603327	.0353654	-1.71	0.090	1300592	.0093938
I						
region						
South	0473932	.040414	-1.17	0.242	1270736	.0322872
Midwest	0035991	.0461239	-0.08	0.938	0945372	.0873389
West	0790752	.0428784	-1.84	0.067	1636144	.0054639
_cons	.2014991	.0506248	3.98	0.000	.101687	.3013112

. predict predprobit (option pr assumed; Pr(visit)) (6276 missing values generated)

. label var predprobit "Predicted Values - Probit"

. tabstat visit predlpm predlogit predprobit, statistics(mean sd min max) col(stat) /// > format(\$9.3f)

variable	1	mean	sd	min	max
visit		0.667	0.471	0.000	1.000
predlpm		0.657	0.202	0.104	1.268
predlogit		0.652	0.220	0.097	0.997
predprobit		0.652	0.216	0.093	0.999

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Analysis/Answers/Assignment3 2016.lo

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