# Homework Solutions Applied Logistic Regression

### WEEK 7

## Exercise 1 (continued):

h. Calculate the Odds Ratio of hyponatremia for a female compared to a male who completes the marathon in the same time.

To calculate the odds ratio, exponentiate the logit:

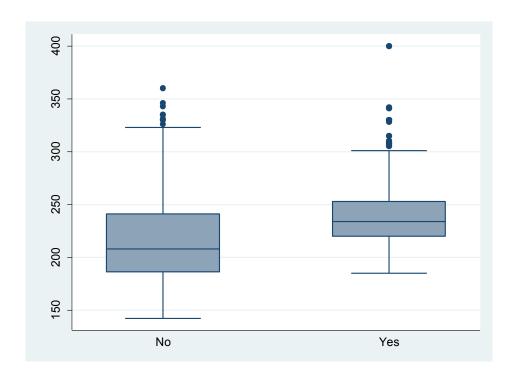
```
. di exp(0.9638)
2.6216398
```

The odds ratio is 2.62.

i. What type of association do you expect between the variables female and runtime? Answer this question before looking at the data, only on the basis of the observed change in the coefficient for female when runtime is entered into the model. Then make a box-plot of runtime by female.

We expect a positive association between female and runtime: on average females will be slower than males. This can be deduced because the coefficient for female decreases when runtime is entered into the model and because runtime has a positive association itself with nas135. Part of the effect of female on nas135 in the univariable model is confounded by the positive association between female and runtime. The box-plot makes clear this association.

. graph box runtime, over(female)



# j. Assess whether there is an interaction between female and runtime

For this part of the analysis, you must first generate an interaction term:

```
. gen femXrun=female*runtime
(11 missing values generated)
```

## Next, fit the regression with the interaction term included:

logit nas135							
Logistic regression  Log likelihood = -162.14884					i2(3)	=	477 36.60 0.0000
					Prob > chi2 = Pseudo R2 =		
nas135	Coef.	Std. Err.	Z	P> z	[95% C	conf.	Interval]
female	1.664386	1.666064	1.00	0.318	-1.6010	39	4.929811
runtime	.015392	.0042988	3.58	0.000	.00696	66	.0238175
femXrun	0028449					29	.010203
_cons	-6.006664	1.067652	-5.63	0.000	-8.0992	24	-3.914104
NOTE: An alternativ logit nas135			log				
	i.female##c	.runtime, no	log	LR ch Prob	er of obs .i2(3) > chi2 lo R2	=	477 36.60 0.0000 0.1014
logit nas135 ogistic regre og likelihood	i.female##c	.runtime, no		LR ch Prob Pseud	i2(3) > chi2 lo R2	= = =	36.60 0.0000 0.1014
logit nas135 cogistic regre cog likelihood nas135	ssion = -162.1488	.runtime, no  4  Std. Err.		LR ch Prob Pseud	i2(3) > chi2 lo R2	= = = :	36.60 0.0000 0.1014 Interval]
logit nas135 Logistic regre Log likelihood nas135  + 1.female	ssion  = -162.14884  Coef.	.runtime, no  4  Std. Err.  1.666064	z 1.00	LR ch Prob Pseud P> z	i2(3) > chi2 lo R2  [95% C	= = = :: :onf.	36.60 0.0000 0.1014 Interval]
logit nas135 logistic regre log likelihood logistic regre log likelihood logistic regre logistic	ssion  = -162.14884  Coef.  1.664386	.runtime, no  4  Std. Err.  1.666064	z 1.00	LR ch Prob Pseud P> z	i2(3) > chi2 lo R2  [95% C	= = = :: :onf.	36.60 0.0000 0.1014 Interval]
logit nas135 logistic regre log likelihood nas135   logistic regre	ci.female##c ssion  = -162.14884	.runtime, no  4  Std. Err.  1.666064 .0042988	z 1.00 3.58	LR ch   Prob   Pseud   Pseud	i2(3) > chi2 lo R2  [95% C1.6010 .00696	= = = Conf.	36.60 0.0000 0.1014  Interval]  4.929811 .0238175
logit nas135 logistic regre log likelihood logistic regre log likelihood logistic regre logistic	ci.female##c ssion  = -162.14884	.runtime, no  4  Std. Err.  1.666064 .0042988	z 1.00	LR ch   Prob   Pseud   Pseud	i2(3) > chi2 lo R2  [95% C1.6010 .00696	= = = Conf.	36.60 0.0000 0.1014 Interval]

The interaction term between the 2 variables is far from significant (p=0.669>>0.05). There is no interaction between these 2 variables.

k. Add to the model that contains **female** and **runtime** a dichotomous variable **wgain** which takes the value of 0 if **wtidff** ≤ 0, and the value of 1 if **wtidff** > 0. Test for interaction between **female** and **wgain**.

First, generate a new variable (wgain), making sure to generate missing variables for wtgain in the event that observations of wtdiff that are missing (Stata recognizes missing variables as having a value of positive infinity). Run a regression with wgain included.

Generate an interaction term between gender and weight gain. Run a regression with the interaction term included as well:

<pre>. gen femXgain=female*wgain (33 missing values generated)</pre>										
. logit nas135	. logit nas135 female runtime wgain femXgain, nolog									
Logistic regree		3		LR ch Prob		=	449 70.64 0.0000 0.2091			
		Std. Err.			[95% C	onf.	Interval]			
female   runtime   wgain	1.500834 .0168796 2.401 -1.201856	.52248 .0038896 .5119424 .6609401	2.87 4.34 4.69	0.004 0.000 0.000 0.069	.00925 1.3976	61 12 75				

The coefficient for the interaction term is significant at the 10% level (p=0.069>0.1)

 On the basis of the model with the interaction term, calculate the Odds Ratios of hyponatremia for males who gain weight as compared to those who don't. Repeat this exercise for a female. Interpret your findings.

#### Based on this model, the logit for females is

$$\beta_0 + \beta_1(female) + \beta_2(runtime) + \beta_3(wgain) + \beta_4(fem \times gain)$$

So, for females, the log odds ratio (= logit difference) comparing those with weight gain vs those without is  $\left[ \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1(1) + \boldsymbol{\beta}_2(runtime) + \boldsymbol{\beta}_3(1) + \boldsymbol{\beta}_4(1 \times 1) \right] - \left[ \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1(1) + \boldsymbol{\beta}_2(runtime) + \boldsymbol{\beta}_3(0) + \boldsymbol{\beta}_4(1 \times 0) \right]$   $= \boldsymbol{\beta}_3 + \boldsymbol{\beta}_4 = 2.401 - 1.202$ 

and the odds ratio =  $e^{2.401-1.202}$  = 3.317

For males, the log odds ratio (= logit difference) comparing those with weight gain vs those without is:

$$[\beta_0 + \beta_1(0) + \beta_2(runtime) + \beta_3(1) + \beta_4(0 \times 1)] - [\beta_0 + \beta_1(0) + \beta_2(runtime) + \beta_3(0) + \beta_4(0 \times 0)]$$

$$= \beta_3 = 2.401$$

and the odds ratio =  $e^{2.401}$  = 11.034

```
. di exp(2.401)
11.034205

. di exp(2.401-1.202)
3.3167985
```

A male who experiences weight gain during a marathon has an odds of hyponatremia about 11 times higher than that of a male who does not gain weight. On the other hand, a female who experiences weight gain during a marathon has an odds of hyponatremia about 3 times higher than that of a female who does not gain weight.

m. Compare using the Likelihood Ratio test the model with female and runtime with a model with female, runtime, wgain, urinat3p and bmi. (Hint: the 2 models must be fitted on the same set of observations. Be aware of missing values in some of these variables). How many degrees of freedom does the test statistic have?

First, generate a subpopulation (nomiss) for all of the observations without missing variables (Note:"!=." is code for "does not equal to missing")

```
. gen nomiss=0
. replace nomiss=1 if female!=. & urin!=. &bmi!=. &wgain!=. &runtime!=.
(442 real changes made)
```

Run the full model, and store the estimates for the model under the name "A" using the command "est store A"

ogistic regres	ssion						442
	LR chi2(5) = Prob > chi2 =			0.0000			
og likelihood	= -131.6162	7		Pseud	o R2	=	0.1979
		Std. Err.			[95% (	Conf.	Interval]
		.4155214			05474	197	1.574064
runtime	.0147009	.0048388	3.04	0.002	.00521	71	.0241848
wgain	1.735328	.330983	5.24	0.000	1.0866	513	2.384043
bmi	0041517	.0742347	-0.06	0.955	14964	191	.1413456
		.5514101					
cons I	-6.56561	1.599794	-4.10	0.000	-9.7011	49	-3.43007

Run a second regression with only female and runtime as independent variables, making sure to exclude all missing variables by limiting the analysis to the subpopulation ("nomiss==1"). Store the estimates of the model under the name "B" through the command "est store B"

. logit nas135	female runt	ime if nomis	s==1, nol	log			
Logistic regres	ssion				r of obs		442
					i2(2)		
				Prob	> chi2		
Log likelihood	= -148.2400	5		Pseud	o R2	=	0.0966
	Coef.				-	onf.	Interval]
	.8739657					86	1.471845
runtime	.0152055	.0035895	4.24	0.000	.00817	02	.0222408
cons I	-5.959965	.8973516	-6.64	0.000	-7.7187	42	-4.201188

Run a likelihood ratio test comparing the estimates of the full model (A) to those of the reduced model (B) through the command "Irtest B A"

. lrtest B A		
Likelihood-ratio test (Assumption: B nested in A)	LR chi2(3) = Prob > chi2 =	33.25 0.0000

The LR test is highly significant. The test uses 3 degrees of freedom, which is the difference in the number of covariates (5-2=3). The model with 5 covariates is better than the one with 2 covariates.