Overview. Long and Freese discuss alternative ways of standardizing variables that may help with interpretation. They primarily talk about these techniques with regards to logistic, multinomial logistic, and ordinal regression models, but they may be useful for OLS regression as well. Their listcoef command illustrates these different alternatives. I’ll first present some preliminary results that will make it easier to understand what listcoef is doing.

. use https://www3.nd.edu/~rwilliam/statafiles/glm-logit.dta, clear
. sum

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>grade</td>
<td>32</td>
<td>.34375</td>
<td>.4825587</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>gpa</td>
<td>32</td>
<td>3.117188</td>
<td>.4667128</td>
<td>2.06</td>
<td>4</td>
</tr>
<tr>
<td>tuce</td>
<td>32</td>
<td>21.9375</td>
<td>3.901509</td>
<td>12</td>
<td>29</td>
</tr>
<tr>
<td>psi</td>
<td>32</td>
<td>.4375</td>
<td>.5040161</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

. logit grade gpa tuce i.psi, nolog

Logistic regression

<table>
<thead>
<tr>
<th></th>
<th>Number of obs = 32</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR chi2(3)</td>
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</tr>
<tr>
<td>Prob &gt; chi2</td>
<td>0.0015</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-12.889633</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.3740</td>
</tr>
</tbody>
</table>

| grade       | Coef. | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|-------------|-------|-----------|-------|------|---------------------|
| gpa         | 2.826113 | 1.262941   | 2.24  | 0.025 | .3507938  | 5.301432 |
| tuce        | .0951577 | .1415542   | 0.67  | 0.501 | -.1822835 | .3725988 |
| 1.psi       | 2.378688 | 1.064564   | 2.23  | 0.025 | .29218    | 4.465195 |
| _cons       | -13.02135| 4.931325   | -2.64 | 0.008 | -22.68657 | -3.35613 |

. fitstat

[A lot of output omitted]
. listcoef, std help

logit (N=32): Unstandardized and standardized estimates

Observed SD: 0.4826
Latent SD: 2.6851

|          b        z    P>|z|    bStdX    bStdY   bStdXY     SDofX |
|----------|-----------|----------|------------|------------|--------------|--------|
| gpa      | 2.8261    | 2.238    | 0.025      | 1.319      | 1.053        | 0.491  | 0.467 |
| tuce     | 0.0952    | 0.672    | 0.501      | 0.371      | 0.035        | 0.138  | 3.902 |
| 1.psi    | 2.3787    | 2.234    | 0.025      | 1.199      | 0.886        | 0.447  | 0.504 |
| constant | -13.0213  | -2.641   | 0.008      | .           | .            | .      |

b = raw coefficient
z = z-score for test of b=0
P>|z| = p-value for z-test
bStdX = x-standardized coefficient
bStdY = y-standardized coefficient
bStdXY = fully standardized coefficient
SDofX = standard deviation of X

In the listcoef output, the column labeled b (which the logit command labels as Coef.) gives the unstandardized (metric) coefficients. The columns labeled z and P>|z| are also the same as in the logit output. The other columns (which were presented because I used the std option) give information that is relevant to different types of standardization. The help option added the descriptions of what each part of the output means.

Full Standardization. With full standardization, both the X and the Y* variables are standardized to have a mean of 0 and a standard deviation of 1. It is similar to standardization in OLS regression (with the important difference that Y* is a latent variable and not observed; we’ll see why this is important later). In the listcoef output, the fully standardized coefficients are in the column labeled bStdXY. [NOTE: As fitstat shows, the variance of Y* is 7.21, which means its standard deviation is 2.685 – the same as what listcoef reports.]

The results show you that a 1 standard deviation increase in gpa results, on average, in almost half a standard deviation increase (.4912) in the log odds of getting an A.

If you know the metric coefficients and the standard deviations of the the x’s and y*, you can compute the standardized coefficients the same way you do in OLS:

\[ b'_k = b_k * \frac{s_x}{s_{y*}} \]

So, for example, to get the fully standardized effect of gpa,

\[ b'_{gpa} = b_{gpa} * \frac{s_{gpa}}{s_{y*}} = 2.82611 * \frac{.4667}{2.685} = .4912 \]
**X-Standardization.** An intermediate approach is to standardize only the X variables. In the listcoef output, in the column labeled bStdX, the Xs are standardized but Y* is not. Hence, by standardizing the Xs only, you can see the relative importance of the Xs. We see that a 1 standard deviation increase in gpa produces, on average, a 1.319 increase in the log odds of getting an A. (To get the X-Standardized coefficient, just multiply b_k by the standard deviation of x_k, e.g. for gpa $2.82611 \times .4667 = 1.319$.)

**Y-Standardization.** You can also standardize Y* only. The listcoef column labeled bStdY gives you the coefficients from when Y* is standardized but X is not. A 1 unit increase in gpa produces, on average, a 1.0525 standard deviation increase in Y*. To get the Y-standardized coefficient, just divide b_k by the standard deviation of Y*, e.g. for gpa $2.82611/2.685 = 1.0525$.

If you don’t include the std parameter, after a logistic regression listcoef does a variation of X-standardization, showing you the odds ratios (i.e. the factor change in the odds as X increases):

```bash
   . listcoef

logit (N=32): Factor change in odds

         |          b        z    P>|z|       e^b   e^bStdX     SDofX
-------------+-----------------------------------------------------------
         gpa |     2.8261    2.238    0.025    16.880     3.740     0.467
         tuce |     0.0952    0.672    0.501     1.100     1.450     3.902
        1.psi |     2.3787    2.234    0.025    10.791     3.316     0.504
        constant |   -13.0213   -2.641    0.008         .         .         .
```  

This tells you that a 1 unit increase in gpa multiplies the odds of success by 16.880. A 1 standard deviation increase in gpa multiplies the odds by 3.740. (Recall that the X-standardized coefficient is 1.3190; $\exp(1.3190) = 3.74$.) See the help for listcoef for other options that may be useful.

**Discussion.** The usual argument for using standardized coefficients is that they provide a means for comparing the effects of variables measured in different metrics. This is true here as well. So, for example, you can see that a 1 standard deviation (SD) increase in gpa produces more change in the log odds of getting an A than does a 1 SD increase in tuce. Nevertheless, standardized effects tend to be looked down upon. It makes no sense to think about a one SD increase in a dummy variable like gender. Even for continuous variables, standardized coefficients are not very intuitive, e.g. how many of us think in terms of standard deviations? Worse, they can be very misleading. For example, if the standard deviations of variables differ across groups, the standardization of variables will also differ, causing coefficients to not be comparable across groups (e.g. in one group X might get divided by 10 while in another it gets divided by 7.)

There are, however, some unique concerns when using logistic regression and other GLMs. Unlike Y in OLS regression, the variance of Y* is not fixed; it will change as you add more variables to the model. This can create problems in logistic regression that you do not have with
OLS regression. Some authors (e.g. Winship & Mare, ASR 1984) therefore recommend Y-Standardization or Full-Standardization. We discuss this further in a later handout.

Appendix: Standardized Coefficients in OLS Regression

If you run `listcoef` after the `regress` command, the fully standardized coefficients are the same as the regression standardized coefficients, e.g.

```
webuse nhanes2f, clear
.reg weight height age female black, beta
```

```
Source |       SS       df       MS              Number of obs =   10337
-------------+------------------------------           F(  4, 10332) =  881.52
Model |  620082.606     4  155020.652           Prob > F      =  0.0000
Residual |  1816944.64 10332  175.856044           R-squared     =  0.2544
-------------+------------------------------           Adj R-squared =  0.2542
Total |  2437027.25 10336    235.7805           Root MSE      =  13.261

------------------------------------------------------------------------------
  weight |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
  height |   .7485279     .01966    38.07   0.000                 .470932
  age |   .1237255   .0078948    15.67   0.000                 .138726
  _1.female |  -1.540187   .3721392    -4.14   0.000                -.050091
  _1.black |   3.679295   .4256284     8.64   0.000                 .073476
  _cons |  -59.05337   3.563342   -16.57   0.000                        
------------------------------------------------------------------------------
```

```
.listcoef, std help
```

regress (N=10337): Unstandardized and standardized estimates

```
Observed SD: 15.3551
SD of error: 13.2611
```

```
|                      | b     | t     | P>|t| | bStdX | bStdY | bStdXY | SDofX |
|----------------------|-------|-------|------|-------|-------|--------|-------|
| height               | 0.7485| 38.074| 0.000| 7.231 | 0.049 | 0.471  | 9.660 |
| age                  | 0.1237| 15.672| 0.000| 2.130 | 0.008 | 0.139  | 17.217|
| _1.female            | -1.540| -4.139| 0.000| -0.769| -0.100| -0.050 | 0.499 |
| _1.black             | 3.6793| 8.644 | 0.000| 1.128 | 0.240 | 0.073  | 0.307 |
| _cons                | -59.053| -16.572| 0.000| .      | .      | .      |       |
```

Note that, in OLS, while full standardization is frequently done, X-Standardization alone is enough to achieve the goal of comparing the effects of Xs measured in different metrics, and may be easier to interpret since Y is left in its original metric. So, for example, we can see that a 1 standard deviation in height results, in average, on a 7.23 kilogram increase in weight, whereas a 1 standard deviation increase in age results in an average increase of 2.13 kilograms.