

Logistic regression example to accompany

**Hayes, A. F., & Matthes, J. (2009). Computational procedures for probing interactions in OLS and logistic regression: SPSS and SAS implementations. *Behavior Research Methods*, 41, 924-936.**

Hayes and Matthes (2009) give two examples on the use of the macros for probing an interaction in OLS regression. To supplement information in the paper, below we provide a worked example of the use of the macro for probing an interaction in logistic regression.

The data for this example come from a telephone survey of 644 German-speaking residents of Switzerland during a national referendum on the naturalization of immigrants. The outcome variable, *voting intention*, codes how the person reported he or she would vote if the referendum were held that day (1 = vote against the referendum, 2 = vote in favor of the referendum). Voting in favor of the referendum implies a belief that stricter legal procedures should be required for immigrants to attain Swiss citizenship. Voting intention was predicted from measures of *negative emotion* and *issue importance*. Negative emotion was assessed by three questions asking about the extent to which respondents experienced anger, discomfort, or fear when they think about immigrants, scaled from 1 (not at all) to 5 (very much) and aggregated into a single score (higher = more negative emotion). Issue importance was measured with two items, also aggregated into a single score asking how personally and nationally important the issue of naturalization was perceived to be (1 to 5, higher = more important).

The goal of the analysis was to estimate the effect of negative emotion on voting intention, and assess the extent to which this effect is contingent on issue importance. So negative emotion was treated as the focal predictor and issue importance served as the moderator. Sex (male = 1, female = 2) and respondent age (in years) were included as statistical controls. After activating the macro by running the macro command set exactly as is, the command

```
MODPROBE y = vote/x = sex age negemo import.
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estimates a logistic regression model of voting intention from negative emotion, issue importance, and their product, as well as sex and age. In the command syntax, the variable listed last in the “x=” list is treated as the moderator and the variable listed second to last is treated as the focal predictor. All other variables in the list are treated as covariates. The macro automatically recodes the outcome variable 1 and 0, setting the higher code in the data to 1 and the lower code in the data to 0. The “event” modeled is the event coded 1 in the **recoded** data—in this case, voting in favor of the referendum—as opposed to against it.

The output looks as such:

```
Run MATRIX procedure:
SPSS Macro for Probing Interactions in OLS and Logistic Regression

Outcome Variable
  Vote

Focal Predictor Variable
  NegEmo

Moderator Variable
  Import

Coding of binary Y for analysis:
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```

Vote Analysis
1.00 .00
2.00 1.00

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Logistic Regression Summary

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-2LL Model LL McFadden CoxSnell Nagelkrk n
797.7671 93.6085 .1050 .1353 .1805 644.0000

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=====
              b              se              Z              p              Exp(B)              Wald
constant    -.6291          1.1259          -.5588          .5763          .5331          .3122
sex         -.3398          .1722          -1.9736         .0484          .7119          3.8950
age         .0077           .0050           1.5447         .1224          1.0078         2.3861
NegEmo     -.1538          .3995          -.3849         .7003          .8575          .1481
Import     -.3200          .2552          -1.2538        .2099          .7261          1.5719
interact    .2190           .0945           2.3180         .0205          1.2448         5.3730

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Interact is defined as:
NegEmo X Import

```

Conditional Effect of Focal Predictor at Values of the Moderator Variable

```

Import      b          se          Z          p          LLCI (b)          ULCI (b)          Wald
3.2958     .5680     .1215     4.6750    .0000     .3299     .8061     21.8557
4.2112     .7685     .0945     8.1286    .0000     .5832     .9538     66.0747
5.1266     .9689     .1344     7.2076    .0000     .7055     1.2324     51.9499

```

```

Alpha level used for confidence intervals:
.05

```

Moderator values are the sample mean and plus/minus one SD from mean

Warning: One SD above the mean is beyond the available data

Note: For data above, covariates are sets to their sample means

The five variable model fits better than the constant only model, chi-square ( $df = 5$ ) = 93.61,  $p < .001$ . Most important, the interaction between issue importance and negative emotion is statistically significant,  $b = 0.2190$ ,  $p = 0.0205$ . So the relationship between negative emotion and voting intention is contingent on issue importance. Specifically, the positive coefficient for the interaction means that the effect of negative emotion is becoming more positive as issue importance increases. By default, the macro probes the interaction at low (3.2958), moderate (4.2112), and high values (5.1266) of issue importance. However, the output states that the “high” value of 5.1266 is outside of the range of the data (the highest possible value based on the measurement scale is 5, and no observations in the data are as high as 5.1266) so this conditional effect is not interpreted. But observe that the effect is statistically significant at both low and moderate values of importance. That is, the more negative emotion a person feels about immigrants, the more likely the person plans on voting in favor of stricter legal procedures for becoming a Swiss citizen.

The effect could be further probed by specifying precise values of issue importance of interest at which to estimate the effect of negative emotion by using the modval subcommand. For instance, the effect of negative emotion at the lowest value of issue importance (1) can be estimated with the following command:

```

MODPROBE y = vote/x = sex age NegEmo Import/modval = 1.

```

which produces the output below along with the logistic regression model :

Conditional Effect of Focal Predictor at Values of the Moderator Variable							
Import	b	se	Z	p	LLCI (b)	ULCI (b)	Wald
1.0000	.1895	.2647	.7160	.4740	-.3293	.7084	.5126

Among those whose issue importance evaluation is very low, there is no effect of negative emotion on voting intention,  $b = 0.1895$ ,  $p = 0.4740$ .

The Johnson-Neyman technique can be used to ascertain where on the issue importance continuum the effect of negative emotion transitions between statistically significant and not significant. By default, “statistically significant” is defined as a  $p$ -value of no greater than 0.05, although this could be changed by the user with the ALPHA subcommand. To implement the Johnson-Neyman technique, the JN subcommand is used:

**MODPROBE y = vote/x = sex age NegEmo Import/JN = 1.**

In addition to the logistic regression model, the macro produces the output below, which reveals that the region of significance for the effect of negative emotion is issue importance of 2.1706 or higher. The effect of negative emotion on voting intention is significantly positive at or above 2.1706, but nonsignificant below that.

Moderator Value(s) Defining Nonsimultaneous Johnson-Neyman Significance Region(s)  
2.1706

Conditional Effect of Focal Predictor at Values of Moderator Variable							
Import	b	se	Z	p	LLCI (b)	ULCI (b)	Wald
1.0000	.1895	.2647	.7160	.4740	-.3293	.7084	.5126
1.2000	.2168	.2496	.8685	.3851	-.2724	.7059	.7543
1.4000	.2440	.2345	1.0403	.2982	-.2157	.7037	1.0822
1.6000	.2712	.2196	1.2349	.2169	-.1592	.7017	1.5250
1.8000	.2985	.2049	1.4568	.1452	-.1031	.7000	2.1223
2.0000	.3257	.1903	1.7116	.0870	-.0473	.6986	2.9294
2.1706	.3489	.1780	1.9600	.0500	.0000	.6978	3.8415
2.2000	.3529	.1759	2.0060	.0449	.0081	.6977	4.0239
2.4000	.3801	.1619	2.3485	.0188	.0629	.6974	5.5154
2.6000	.4074	.1482	2.7493	.0060	.1170	.6978	7.5586
2.8000	.4346	.1350	3.2201	.0013	.1701	.6991	10.3690
3.0000	.4618	.1224	3.7731	.0002	.2219	.7017	14.2366
3.2000	.4891	.1107	4.4181	.0000	.2721	.7060	19.5198
3.4000	.5163	.1002	5.1551	.0000	.3200	.7126	26.5750
3.6000	.5435	.0912	5.9612	.0000	.3648	.7222	35.5364
3.8000	.5708	.0843	6.7730	.0000	.4056	.7359	45.8733
4.0000	.5980	.0800	7.4777	.0000	.4413	.7547	55.9159
4.2000	.6252	.0787	7.9439	.0000	.4710	.7795	63.1049
4.4000	.6525	.0806	8.0931	.0000	.4944	.8105	65.4982
4.6000	.6797	.0855	7.9498	.0000	.5121	.8473	63.1994
4.8000	.7069	.0929	7.6115	.0000	.5249	.8890	57.9351
5.0000	.7342	.1022	7.1826	.0000	.5338	.9345	51.5901

Alpha level used for Johnson-Neyman method and confidence intervals:  
.05