Presenting Results with SDIs

All examples below are based on the following logistic regression analysis with simulated data. The *sdi_betaDo* do-file contains the code to reproduce the data.

Table 1: Logistic regression results with simulated data

Regressor	
x	-0.36**
	(0.16)
Constant	2.14***
	(0.30)
Log Likelihood	-470.47
Number of Observations	1000

* p < 0.10; ** p < 0.05; *** p < 0.01 (two-tailed test)

Example 1

Let us say we want to evaluate a simple hypothesis: the likelihood of y decreases as x increases. If there were empirical support for this expectation, the probability of y at low x values would be statistically higher than the probability of y at high x values. To test this hypothesis, we typically compare the predicted probability at the min and max values of x, which can be computed via the `margins` command. Here we focus on the lower and upper range values of x, but the discussion applies to any pair of theoretically relevant x values.

```
. sum x, meanonly

. local r1 = r(min)

. local r2 = r(max)

. local u4 = (`r2'-`r1')/3 // unit increase

.
. margins, at(x=(`r1' `r2')) post noatlegend

Adjusted predictions                            Number of obs     =      1,000
Model VCE    : OIM

Expression   : Pr(y), predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _at |
          1  |   .8554046   .0185899    46.01   0.000      .818969    .8918402
          2  |    .761951   .0313105    24.34   0.000     .7005836    .8233184
------------------------------------------------------------------------------

. nlcom _b[2._at]-_b[1._at]

       _nl_1:  _b[2._at]-_b[1._at]

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -.0934536   .0433326    -2.16   0.031    -.1783839   -.0085232
------------------------------------------------------------------------------
```

Since the CIs of the probabilities at the min and max x values overlap, we cannot tell whether the two point estimates are distinct. As a result, we need to calculate the difference between the two and check whether the CI of the difference contains zero. If it does not, the two point estimates are statistically distinct. To calculate the difference and its CI, we need to use `nlcom`. As the CI of the difference does not contain zero, the two probabilities are distinct in spite of the CI overlap.

To test our hypothesis employing the `sdi` command, we would type

```
. sdi, xofi(x=(`r1' `r2')) range diff

SDI Results (pairwise comparisons)

    Expression       :         Pr(y), predict()
    Statistic        :         Predictive margins
    Standard errors  :         Delta-method
    Number of obs    =         1,000

    xofi[nterest]
    1._xofi :   x          =         1.000397
    2._xofi :   x          =         2.717659
```

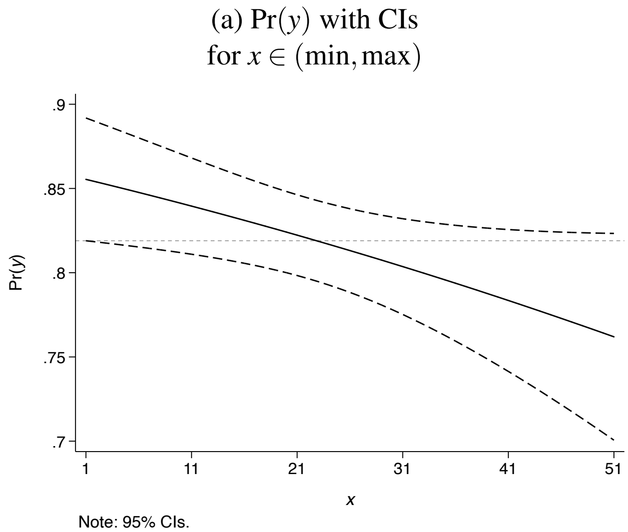
	Statistic	Std. Err.	[Interval	Bounds]	(%) Type
_xofi					
1 (a)	.85540456	.01858994	.82376456	.88704461	91.1 SDI
2 (b)	.76195097	.03131048	.7086606	.81524134	91.1 SDI
(b)vs(a)	-.09345362	.04333263	-.17838399	-.00852323	95 CI

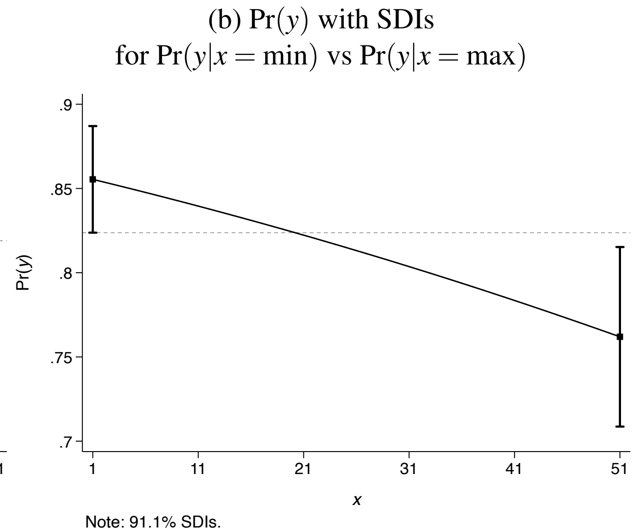
Note: SDIs indicate significance of difference from 0.

As the SDIs do not overlap, we can immediately tell that the probability of y at min and max x values are statistically different. Because we used the `difference` option, `sdi` also reports the difference in estimates with the 95% CI. These estimates are identical to the `nlcom` results.

Since x is a continuous variable, we could graph $\Pr(y)$ with its CIs across the entire range of x (Figure 1a). As before, since the CIs of the probability at the min and max x values overlap, we cannot tell whether the two point estimates are distinct. Figure 1b shows the same predicted probabilities with the appropriate 91.1% SDIs. The lack of overlap indicates that the probability of y at low x values is statistically higher than the probability of y at high x values. We report SDIs only for the two compared estimates to prevent confusion as, arguably, this way is clearer which the comparison of interest is.

Figure 1: The probability of y across the range of x





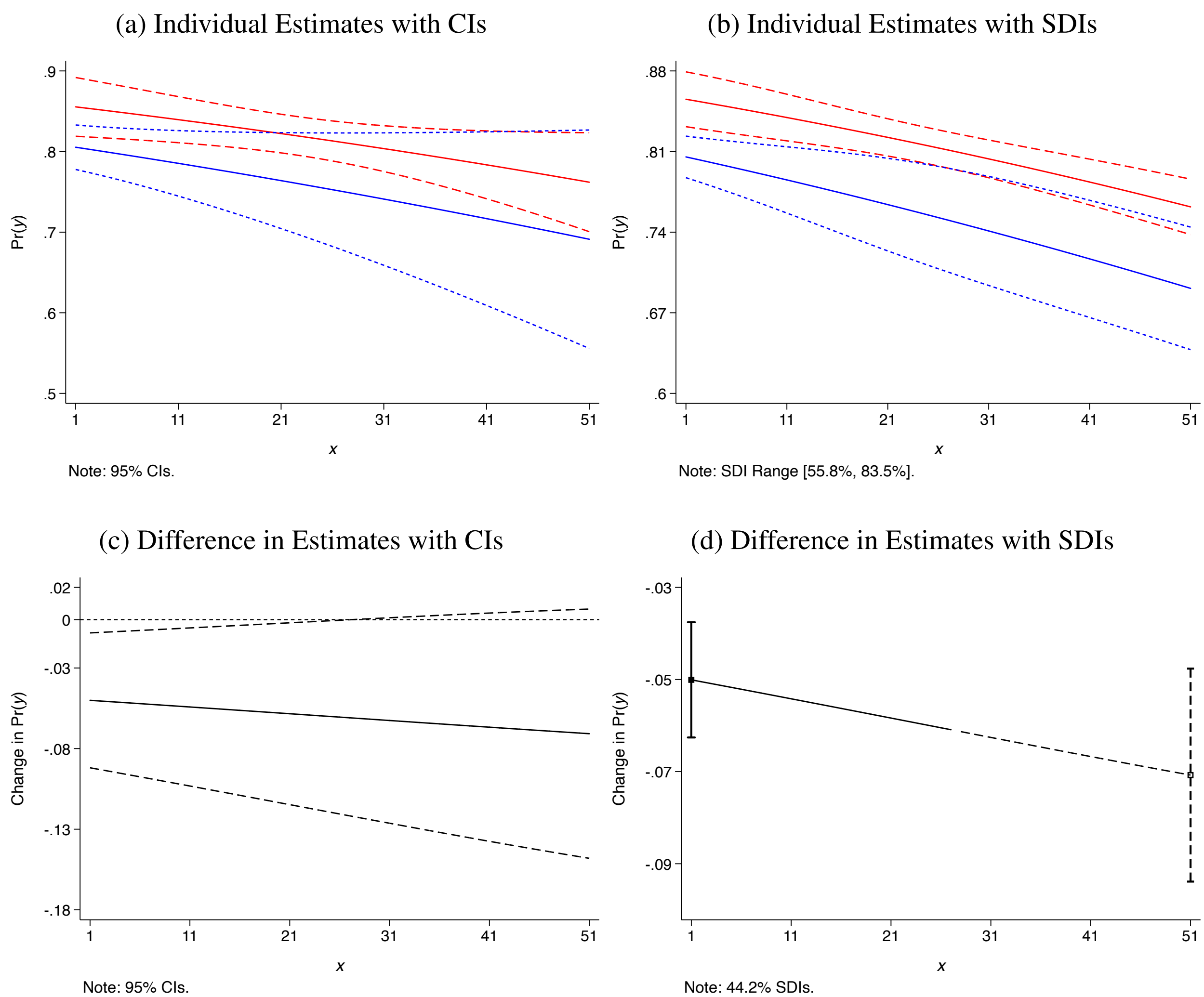
The values outlined in Figure 1a are calculated via `margins`, and the estimates in Figure 1b via the `sdi` command. For simplicity, here we report only 4 estimates. However, we actually estimated $\Pr(y)$ for 51 distinct values of x to ensure that the plot lines are smooth. (The *sdi_betaDo* do-file contains the full code to replicate Figure 1a and 1b.) Note the effect of using the `range` option with the `sdi` command. Instead of computing SDIs for all pairwise comparisons (in the full estimation, which is not shown, there are 51 estimates and 1,275 comparisons in total), only the SDIs for the comparison of the probability at the smallest and largest values of the x range are calculated. The remaining in-between values are reported to facilitate plotting the probability of y across the entire range of x.

```
. margins, at(x=(`r1'(`u4')`r2')) noatlegend

Adjusted predictions                            Number of obs     =      1,000
Model VCE    : OIM

Expression   : Pr(y), predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _at |
          1  |   .8554046   .0185899    46.01   0.000      .818969    .8918402
          2  |   .8281955   .0126348    65.55   0.000     .8034316    .8529593
          3  |   .7970809   .0164056    48.59   0.000     .7649265    .8292352
          4  |    .761951   .0313105    24.34   0.000     .7005836    .8233184
------------------------------------------------------------------------------
. sdi, xofi(x=(`r1'(`u4')`r2')) range

SDI Results (pairwise comparisons)

    Expression        :          Pr(y), predict()
    Statistic         :          Predictive margins
    Standard errors   :          Delta-method
    Number of obs     =          1,000

    xofi[nterest]
    1._xofi :   x          =          1.000397
    2._xofi :   x          =          1.572818
    3._xofi :   x          =          2.145238
    4._xofi :   x          =          2.717659

------------------------------------------------------------------------------
        |     Statistic      Std. Err.      [Interval         Bounds]      (%) Type
--------+---------------------------------------------------------------------
_xofi   |

1       |     .85540456      .01858994      .82376456      .88704461      91.2 SDI
4       |     .76195097      .03131048       .7086606      .81524134      91.2 SDI
2       |     .82819545
3       |     .79708087
------------------------------------------------------------------------------
Note: SDIs indicate significance of difference from 0.
```

Example 2

Apart from comparing predicted probabilities at observed values of *x*, researchers often examine the effect on *y* of a counterfactual increase in *x*. Figure 2a shows the predicted probability with the 95% CI for two scenarios. In red with dashed CI is the probability of *y* across the *x* range, whereas in blue with dotted CI is the predicted probability were *x* to increase by 1 (i.e., *x* + 1). While a 1-unit increase in *x* seems to decrease the probability of *y*, the associated CIs overlap throughout. As a result, the two probabilities may or may not be statistically different.

Figure 2: The effect of a 1-unit increase in *x* on the probability of *y*



The `margins` command to compute the estimates plotted in Figure 2a is

```
. margins, at(x=(`r1'(`u4')`r2')) at(x=(`=`r1'+1'(`u4')`=`r2'+1')) noatlegend

Adjusted predictions                            Number of obs     =      1,000
Model VCE    : OIM

Expression   : Pr(y), predict()
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_at						
1	.8554046	.0185899	46.01	0.000	.818969	.8918402
2	.8281955	.0126348	65.55	0.000	.8034316	.8529593
3	.7970809	.0164056	48.59	0.000	.7649265	.8292352
4	.761951	.0313105	24.34	0.000	.7005836	.8233184
5	.8053314	.0140776	57.21	0.000	.7777399	.8329229
6	.7712199	.0269005	28.67	0.000	.7184959	.8239439
7	.733112	.0461082	15.90	0.000	.6427416	.8234824
8	.691198	.0691405	10.00	0.000	.5556852	.8267109

Much more information can be gleaned from Figure 2b, which shows the predicted probabilities with SDIs. The two probabilities are actually distinct at low values of x, but they are indistinguishable at higher values where the SDIs overlap. Here the SDI level ranges from 55.8% to 83.5% because we need a different level for each $\left[\Pr(y|x), \Pr(y|(x+1))\right]$ pair, where $x \in [\min_x, \max_x]$.

To estimate the values for Figure 2b we type

```
. sdi, xofi(x=(`r1'(`u4')`r2')) nunit(1)

SDI Results (pairwise comparisons)

    Expression        :          Pr(y), predict()
    Statistic         :          Predictive margins
    Standard errors   :          Delta-method
    Nº                :          Comparison reference number
    Number of obs     =          1,000

    xofi[nterest]
    1._xofi :   x          =         1.000397
    2._xofi :   x          =         1.572818
    3._xofi :   x          =         2.145238
    4._xofi :   x          =         2.717659

    n-unit   =   1
```

	Statistic	Std. Err.	[Interval	Bounds]	(%) Type
Nº: _xofi					
1: 1	.85540456	.01858994	.83159828	.87921083	80.0 SDI
1: (1+n)	.80533141	.01407755	.78730375	.82335913	80.0 SDI
2: 2	.82819545	.01263483	.81096029	.84543055	82.8 SDI
2: (2+n)	.77121991	.02690051	.73452502	.80791473	82.8 SDI
3: 3	.79708087	.01640558	.77972788	.81443393	71.0 SDI
3: (3+n)	.73311198	.04610819	.68434107	.78188294	71.0 SDI
4: 4	.76195097	.03131048	.73785698	.7860449	55.9 SDI
4: (4+n)	.69119799	.06914049	.63799322	.74440283	55.9 SDI

Note: SDIs indicate significance of difference from 0.

Alternatively, instead of presenting the two probabilities side by side, we can plot the difference in probability with the 95% CI, Figure 2c. This plot shows that the effect of a 1-unit increase in x is negative and statistically significant at low x values, but it becomes statistically insignificant about midway on the x range. This matches the information conveyed by the individual estimates with SDI graph in Figure 2b. Knowing when the effect becomes statistically insignificant, however, does not elucidate the question of whether the effect varies across the range of x. While a common misconception, a significant estimate can be statistically indistinguishable from another insignificant estimate (i.e., a point estiamte whose 95% CI crosses zero). To compare the effect at min and max x values, we need to report these estimates with SDIs, Figure 2d. Since the 44.2% SDIs overlap, the effect is not statistically different across the x range. Importantly, this information cannot be gleaned from the difference in estimates with 95% CI plot.

By using different patterns, SDI graphs can also outline statistical significance. For example, we can use solid lines for the SDI if the estimate is statistically significant at the 0.05 level and dashed lines otherwise (as an example, see Figure 2d). Thus, the SDI *level* indicates whether the estimates are statistically different from each other, whereas the SDI *pattern* indicates whether they are different from zero. However, one ought not to report this additional piece of information by default. To the contrary, in order to be effective, graphs should display the minimum amount of information required to get the point across.

The estimates for Figure 2c are obtained by running a loop that manually calculates the difference between all relevant pairs from the `margins` output on page 7.

```
. forval i = 1/4 {
  2.         nlcom _b[`=4+`i''._at]-_b[`i'._at]
  3. }

       _nl_1:  _b[5._at]-_b[1._at]
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_nl_1	-.0500732	.0213443	-2.35	0.019	-.0919072	-.0082392

```
       _nl_1:  _b[6._at]-_b[2._at]
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_nl_1	-.0569756	.0275158	-2.07	0.038	-.1109056	-.0030456

```
       _nl_1:  _b[7._at]-_b[3._at]
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_nl_1	-.0639689	.0337373	-1.90	0.058	-.1300929	.002155

```
       _nl_1:  _b[8._at]-_b[4._at]
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_nl_1	-.070753	.0394389	-1.79	0.073	-.1480517	.0065458

Again, we show only 4 of the 51-iteration loop required to compute the difference in estimates via `nlcom`. (For full details see the *sdi_betaDo* do-file.)

The estimates for Figure 2d are obtained via a single line of code, without any loops.

```
. sdi, xofi(x=(`r1'(`u4')`r2')) nunit(1) firstdiff range

SDI Results (pairwise comparisons)

    Expression        :          Pr(y), predict()
    Statistic         :          Contrasts of predictive margins
    Standard errors   :          Delta-method
    Number of obs     =          1,000

    xofi[nterest]
    1._xofi :   x          =          1.000397
    2._xofi :   x          =          1.572818
    3._xofi :   x          =          2.145238
    4._xofi :   x          =          2.717659

    n-unit   =   1
```

	Statistic	Std. Err.	[Interval	Bounds]	(%) Type
_xofi					
[(1+n) vs 1]	-.05007315	.02134426	-.06258616	-.03756014	44.3 SDI
[(4+n) vs 4]	-.07075296	.03943887	-.09387388	-.04763204	44.3 SDI
[(2+n) vs 2]	-.05697556				
[(3+n) vs 3]	-.06396891				

Note: SDIs indicate significance of difference from 0.