

reg sensitivity: A Stata Package for Regression Sensitivity Analysis

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Introduction

Omitted variables are one of the most important threats to the identification of causal effects. In linear models, the well known omitted variable bias formula shows how an omitted variable can bias the regression coefficient on the covariate of interest when that covariate is correlated with the omitted variable. Since it is often implausible to assume that data has been collected on every relevant variable, applied research is often vulnerable to this bias. Nonetheless, omitted variable bias can be quantified under various alternative assumptions about the relationship between the omitted variable and the covariate of interest. Using these techniques, researchers can analyze how sensitive their results are to omitted variable bias.

Several methods of sensitivity analysis for linear models have been proposed in the literature. The **reg sensitivity** package implements the methods proposed in Diegert, Masten, and Poirier (2022), Oster (2019), and Masten and Poirier (2022). In each of these papers, the authors define a set of sensitivity parameters which index relaxations of the assumption that the covariate of interest is uncorrelated with any unobserved variables. The parameter of interest is β_{long} , the coefficient on that covariate of interest in the infeasible regression that includes the unobserved variables. Using this framework, we can ask two questions:

1. What is the set of parameter estimates for β_{long} which are consistent with the relaxed assumptions? That is, what are bounds on the value of β_{long} under the alternate assumptions?
2. How much can we relax the exogeneity assumption before a hypothesis about β_{long} is overturned? This is called the *breakdown point*: the maximum relaxation of the baseline assumption before the hypothesis is overturned.

reg sensitivity can be used to perform both of these sensitivity analyses using the sensitivity parameters defined in Diegert, Masten, and Poirier (2022), Oster (2019), and Masten and Poirier (2022).

Getting Started

We will illustrate how to use **reg sensitivity** with data from Bazzi, Fiszbein, and Gebresilasse (2020), which is used in the empirical application in Diegert, Masten, and Poirier (2022). One of the datasets used in Bazzi, Fiszbein, and Gebresilasse (2020) is included with the package, and can be loaded using the **sysuse** command:

```
. sysuse bfg2020, clear
```

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The specification in column (7) of Table III in Bazzi, Fiszbein, and Gebresilasse (2020) and replicated in Diegert, Masten, and Poirier (2022) is as follows:

```
. local y avgrep2000to2016
. local x tye_tfe890_500kNI_100_16
. local w1 log_area_2010 lat lon temp_mean rain_mean elev_mean d_coa d_riv d_lak ave_gyi
. local w0 i.statea
. local w `w1' `w0'
. local SE cluster(km_grid_cel_code)
. reg `y' `x' `w', `SE'
```

```
Linear regression              Number of obs   =      2,036
                              F(39, 379)       =          .
                              Prob > F         =          .
                              R-squared        =      0.3321
                              Root MSE     =      9.6368
```

(Std. err. adjusted for 380 clusters in km_grid_cel_code)

| avgrep2000to2016 | Robust | | t | P> t | [95% conf. interval] | |
|--------------------------|-------------|-----------|-------|-------|----------------------|-----------|
| | Coefficient | std. err. | | | | |
| tye_tfe890_500kNI_100_16 | 2.054759 | .3491648 | 5.88 | 0.000 | 1.368217 | 2.741302 |
| log_area_2010 | .2758775 | .979906 | 0.28 | 0.778 | -1.650856 | 2.202611 |
| lat | 2.26515 | 1.101151 | 2.06 | 0.040 | .1000189 | 4.430281 |
| lon | .0108189 | .2913783 | 0.04 | 0.970 | -.5621017 | .5837395 |
| temp_mean | 1.62737 | 1.068132 | 1.52 | 0.128 | -.4728361 | 3.727577 |
| rain_mean | .0164826 | .0046086 | 3.58 | 0.000 | .007421 | .0255442 |
| elev_mean | .0154764 | .0037786 | 4.10 | 0.000 | .0080468 | .022906 |
| d_coa | 9.83e-06 | 3.76e-06 | 2.62 | 0.009 | 2.45e-06 | .0000172 |
| d_riv | .0000307 | 9.91e-06 | 3.10 | 0.002 | .0000112 | .0000502 |
| d_lak | 3.05e-07 | 4.45e-06 | 0.07 | 0.945 | -8.44e-06 | 9.05e-06 |
| ave_gyi | -3.779807 | 10.81002 | -0.35 | 0.727 | -25.03493 | 17.47532 |
| statea | | | | | | |
| 5 | -4.213545 | 3.386398 | -1.24 | 0.214 | -10.87203 | 2.444936 |
| 8 | -27.31682 | 6.246914 | -4.37 | 0.000 | -39.59977 | -15.03387 |
| 12 | 4.627587 | 3.354655 | 1.38 | 0.169 | -1.968479 | 11.22365 |
| 13 | .5398875 | 2.643504 | 0.20 | 0.838 | -4.657883 | 5.737658 |
| 17 | -10.25822 | 3.787414 | -2.71 | 0.007 | -17.7052 | -2.811248 |
| 18 | -5.924452 | 3.497393 | -1.69 | 0.091 | -12.80118 | .9522727 |
| 19 | -18.02705 | 4.514016 | -3.99 | 0.000 | -26.9027 | -9.151398 |
| 20 | 1.598741 | 4.633634 | 0.35 | 0.730 | -7.512109 | 10.70959 |
| 21 | -.504168 | 3.185907 | -0.16 | 0.874 | -6.768436 | 5.7601 |
| 22 | .8939823 | 3.276872 | 0.27 | 0.785 | -5.549145 | 7.337109 |
| 26 | -14.06314 | 4.40552 | -3.19 | 0.002 | -22.72546 | -5.400816 |
| 27 | -18.10308 | 4.821495 | -3.75 | 0.000 | -27.58331 | -8.622851 |
| 28 | -6.930918 | 3.675983 | -1.89 | 0.060 | -14.15879 | .2969573 |
| 29 | -4.170334 | 3.902039 | -1.07 | 0.286 | -11.84269 | 3.502024 |
| 31 | -1.342615 | 4.73751 | -0.28 | 0.777 | -10.65771 | 7.97248 |
| 35 | -40.78007 | 9.264248 | -4.40 | 0.000 | -58.99583 | -22.56431 |
| 36 | -9.821649 | 4.68884 | -2.09 | 0.037 | -19.04105 | -.6022507 |
| 37 | -13.53756 | 4.241671 | -3.19 | 0.002 | -21.87772 | -5.197404 |
| 38 | -11.98193 | 5.512474 | -2.17 | 0.030 | -22.82079 | -1.143061 |
| 39 | -6.190808 | 3.655508 | -1.69 | 0.091 | -13.37843 | .9968088 |
| 40 | 13.60029 | 4.880539 | 2.79 | 0.006 | 4.003963 | 23.19661 |
| 42 | -3.14623 | 4.426406 | -0.71 | 0.478 | -11.84962 | 5.557161 |
| 46 | -11.84706 | 5.101547 | -2.32 | 0.021 | -21.87794 | -1.816175 |
| 47 | -3.541445 | 2.794141 | -1.27 | 0.206 | -9.035406 | 1.952515 |
| 48 | 12.82591 | 4.174157 | 3.07 | 0.002 | 4.618502 | 21.03331 |
| 51 | -.8116892 | 4.047756 | -0.20 | 0.841 | -8.770561 | 7.147182 |
| 54 | -3.243583 | 3.570236 | -0.91 | 0.364 | -10.26353 | 3.776369 |
| 55 | -18.92918 | 4.503985 | -4.20 | 0.000 | -27.78511 | -10.07325 |
| 56 | -19.02288 | 9.729311 | -1.96 | 0.051 | -38.15307 | .1073112 |

| | | | | | | |
|--------------------|-----------|----------|-------|-------|-----------|----------|
| <code>_cons</code> | -73.53523 | 57.84708 | -1.27 | 0.204 | -187.2766 | 40.20618 |
|--------------------|-----------|----------|-------|-------|-----------|----------|

Without a subcommand `regsensitivity` performs two sensitivity analyses, one from Diegert, Masten, and Poirier (2022), and one from Oster (2019):

```
. regsensitivity `y' `x' `w', compare(`w1')
```

Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta > 0 | Breakdown point | = | 80.4% |
| Other Params | : cbar = 1, rybar = +inf | | | |

| rxbar | Beta |
|-------|--------------------|
| 0.000 | [2.0548, 2.0548] |
| 0.100 | [1.9042, 2.2053] |
| 0.201 | [1.7488, 2.3607] |
| 0.301 | [1.5830, 2.5266] |
| 0.402 | [1.3991, 2.7104] |
| 0.502 | [1.1855, 2.9240] |
| 0.602 | [0.9216, 3.1879] |
| 0.703 | [0.5647, 3.5448] |
| 0.803 | [0.0018, 4.1077] |
| 0.904 | [-1.2579, 5.3675] |
| 0.989 | [-inf, +inf] |

Regression Sensitivity Analysis, Breakdown Frontier

| | |
|------------|----------------------------|
| Analysis | : Oster (2019) |
| Treatment | : tye_tfe890_500kNI_100_16 |
| Outcome | : avgrep2000to2016 |
| Hypothesis | : Beta != 0 |

| R-squared(long) | Delta(Breakdown) |
|-----------------|------------------|
| 0.137 | 2328.8% |
| 1.000 | 170.4% |

To explore the output, we will consider each sensitivity analysis separately.

Diegert, Masten, and Poirier (2022)

Diegert, Masten, and Poirier (2022) consider the model:

$$Y = \beta_{\text{long}}X + \gamma'_0W_0 + \gamma'_1W_1 + \gamma_2W_2 + Y^{\perp X, W},$$

where (Y, X, W_0, W_1) are observed and W_2 is an omitted variable that is potentially correlated with (X, W_0, W_1) .¹ Restrictions on the joint distribution of (Y, X, W_0, W_1, W_2) are governed by three scalar

¹We denote the coefficient on X by β_{long} because it is the regression coefficient in the infeasible “long” regression of Y on $(1, X, W_0, W_1, W_2)$. This helps distinguish it from β_{med} , the coefficient on X in the regression of Y on $(1, X, W_0, W_1)$, and from β_{short} , the coefficient on X in the regression of Y on $(1, X, W_0)$.

sensitivity parameters, $(\bar{r}_X, \bar{r}_Y, \bar{c})$. Given the joint distribution of the observed variables, (Y, X, W_0, W_1) , and the values of the sensitivity parameters, Diegert, Masten, and Poirier (2022) show how to compute the upper and lower bounds on the identified set for β_{long} , denoted by $\mathcal{B}_I(\bar{r}_X, \bar{r}_Y, \bar{c})$. The identified set is the set of values of β_{long} which are consistent with the distribution of observed data and the maintained assumptions. When $\bar{r}_X > 0$ and $\bar{r}_Y > 0$, β_{long} is not point identified, so we instead estimate these bounds. For more details about the definitions and interpretation of the sensitivity parameters, see Diegert, Masten, and Poirier (2022).

regsensitivity bounds can be used with the option **dmp** to calculate the upper and lower bounds of $\mathcal{B}_I(\bar{r}_X, \bar{r}_Y, \bar{c})$. The basic syntax for **regsensitivity** is similar to the **regress** command and its variants:

```
regsensitivity bounds depvar indepvar controls, options...,
```

where *depvar* is the dependent variable, Y , and *indepvar controls* are the independent variables, (X, W_0, W_1) . Unlike **regress**, the order of the independent variables matter in the call to **regsensitivity**. The first variable, *indepvar*, is X , the variable of interest for which the sensitivity analysis is conducted while *controls* are additional variables included in the model which are not of interest.

By default, **regsensitivity bounds** calculates the bounds for a range of values of \bar{r}_X holding \bar{c} and \bar{r}_Y fixed. The defaults are to set $\bar{c} = 1$ and $\bar{r}_Y = +\infty$. To specify a different value of \bar{c} , use the **cbar** option. For example,

```
. regsensitivity bounds `y' `x' `w', compare(`w1') cbar(.1)
```

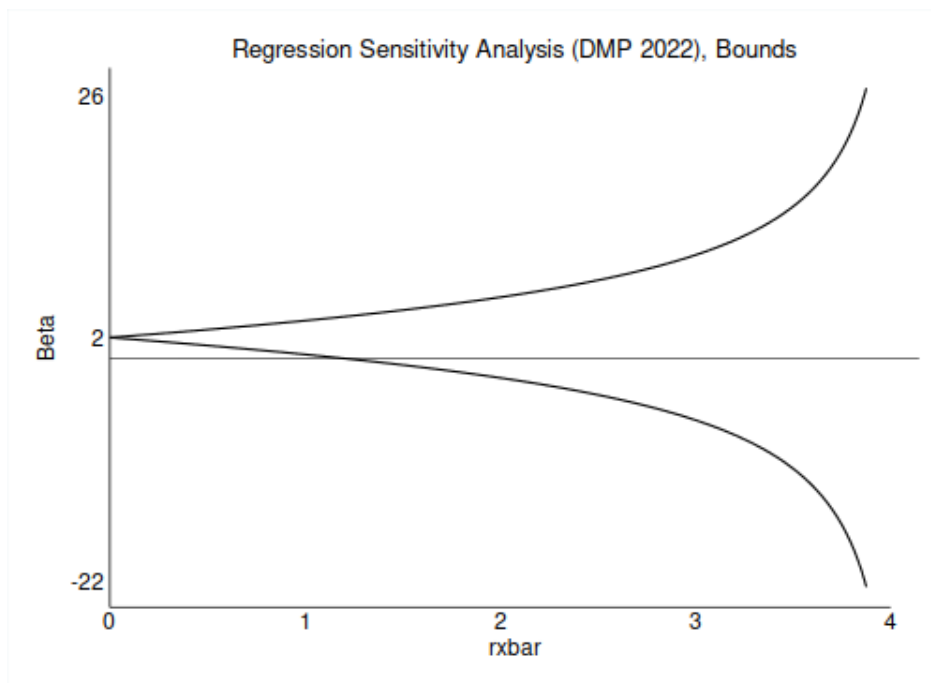
Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta > 0 | Breakdown point | = | 119% |
| Other Params | : cbar = .1, rybar = +inf | | | |

| rxbar | Beta |
|-------|-------------------|
| 0.000 | [2.05, 2.05] |
| 0.415 | [1.41, 2.70] |
| 0.829 | [0.70, 3.41] |
| 1.244 | [-0.10, 4.21] |
| 1.658 | [-1.03, 5.14] |
| 2.073 | [-2.15, 6.26] |
| 2.488 | [-3.56, 7.67] |
| 2.902 | [-5.51, 9.62] |
| 3.317 | [-8.64, 12.75] |
| 3.731 | [-15.85, 19.96] |
| 4.063 | [-inf, +inf] |

To plot the results, use the **plot** subcommand,

```
. regsensitivity plot
```



Notice that in the call to `regsensitivity bounds`, we also included an option `compare(varlist)`. This specifies which of the variables in the *controls* are included in W_1 rather than W_0 . These are referred to as the *comparison controls* because they are the variables used to calibrate the sensitivity parameters, $(\bar{r}_X, \bar{r}_Y, \bar{c})$. For more details, see section 3.3 in Diegert, Masten, and Poirier (2022).

By including more variables in the comparison controls, the identified set will tend to be larger for a given value of the sensitivity parameters. For example, if the `compare` option is omitted, then all the control variables are included in W_1 :

```
. regsensitivity bounds `y' `x' `w', cbar(.1)
```

Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.708 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.027 |
| | | R2(medium) | = | 0.332 |
| | | Var(Y) | = | 136.320 |
| | | Var(X) | = | 1.257 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta > 0 | Breakdown point | = | 29.7% |
| Other Params | : cbar = .1, rybar = +inf | | | |

| rxbar | Beta |
|-------|-------------------|
| 0.000 | [2.05, 2.05] |
| 0.134 | [1.15, 2.96] |
| 0.269 | [0.20, 3.90] |
| 0.403 | [-0.82, 4.93] |
| 0.538 | [-1.97, 6.08] |
| 0.672 | [-3.32, 7.42] |
| 0.806 | [-4.97, 9.08] |
| 0.941 | [-7.21, 11.32] |
| 1.075 | [-10.67, 14.78] |
| 1.210 | [-18.07, 22.17] |

With all the controls included in W_1 , the identified set becomes \mathbb{R} at $\bar{r}_X = 1.336$, compared to $\bar{r}_X = 4.063$ when W_1 excludes the state fixed effects (*statea*). To directly compare the bounds under the two choices of W_1 , we can manually set the values of `rxbar` to be the same in each case. The output table from the last call to `regsensitvity bounds` are stored in `e(idset_table)`. We can extract the values of `rxbar` from these and rerun the analysis with W_1 excluding state fixed effects as follows:

```
. forvalues i=1/11{
2.     local rxbar `rxbar' `=e(idset_table)[`i', 1]'
3. }

. regsensitvity bounds `y' `x' `w', compare(`w1') cbar(.1) rxbar(`rxbar')
```

Regression Sensitivity Analysis, Bounds

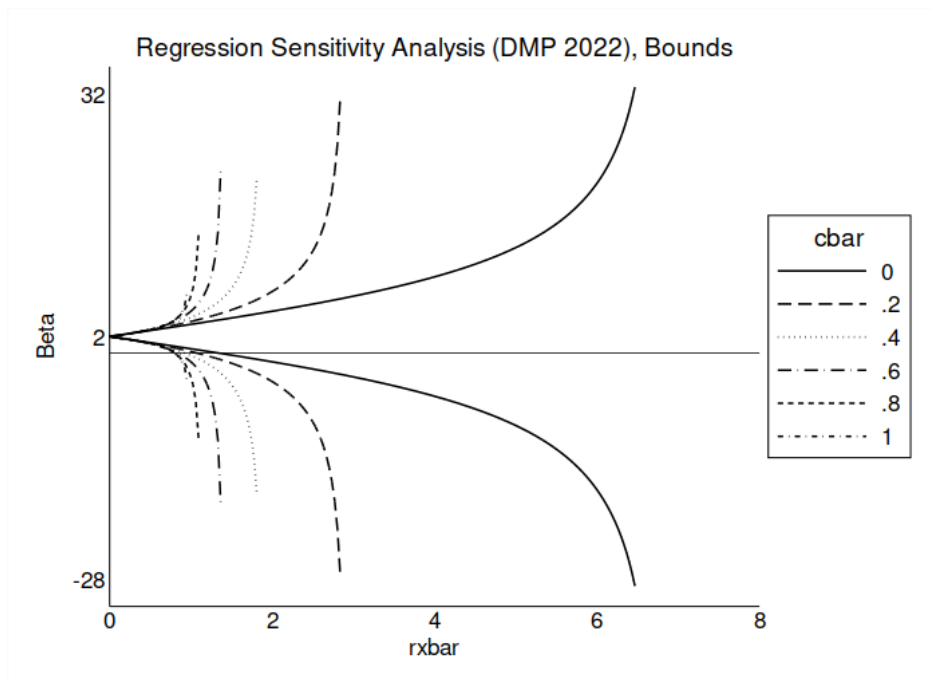
| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta > 0 | Breakdown point | = | 119% |
| Other Params | : cbar = .1, rybar = +inf | | | |

| rxbar | Beta |
|-------|--------------------|
| 0.000 | [2.0548, 2.0548] |
| 0.134 | [1.8525, 2.2570] |
| 0.269 | [1.6444, 2.4651] |
| 0.403 | [1.4299, 2.6796] |
| 0.538 | [1.2085, 2.9010] |
| 0.672 | [0.9794, 3.1301] |
| 0.806 | [0.7420, 3.3676] |
| 0.941 | [0.4952, 3.6143] |
| 1.075 | [0.2381, 3.8714] |
| 1.210 | [-0.0304, 4.1399] |
| 1.336 | [-0.2937, 4.4032] |

Comparing each line of the table to the previous call where all the *controls* were included in W_1 , we can see that the bounds are much tighter for each value of \bar{r}_X .

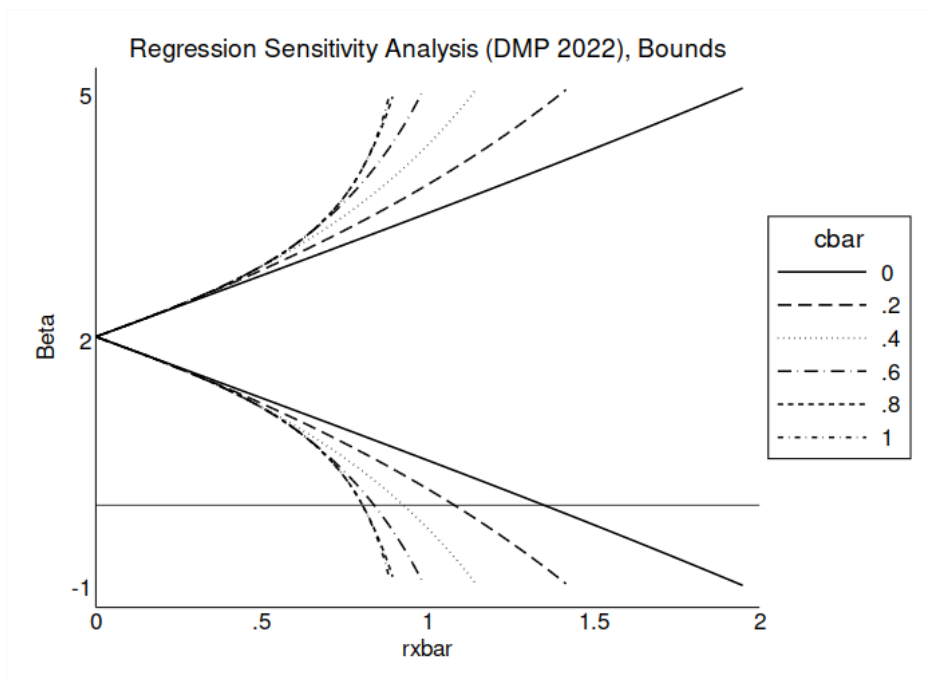
To compare multiple values of \bar{c} , a `numlist` can be given in the `cbar` option. With multiple values of \bar{c} , the command will show a plot rather than displaying the results in the console.

```
. regsensitvity bounds `y' `x' `w', compare(`w1') cbar(0(.2)1)
```



By default, the plot will try to show where the identified set becomes \mathbb{R} for each value of \bar{c} . For this example, the plot is dominated visually by the identified set for $\bar{c} = 0$. To see better where the identified set intersects with 0, we can rerun the analysis restricting the range of \bar{r}_X .

```
. regsensitivity bounds `y' `x' `w', compare(`w1') cbar(0(.2)1) rxbar(0(.2)2) plot
```



Breakdown Frontier

The output of `regsensitivity bounds` shows a *breakdown point* for a given hypothesis about the parameter β_{long} . For a hypothesis $\beta_{\text{long}} \in B \subseteq \mathbb{R}$, the breakdown point is the smallest value of the sensitivity parameter \bar{r}_X for which the hypothesis does not hold for every β value in the identified set. Formally,

$$\bar{r}_X^{\text{bp}}(\bar{r}_Y, \bar{c}; B) = \inf\{\bar{r}_X \geq 0 : b \in \mathcal{B}_I(\bar{r}_X, \bar{r}_Y, \bar{c}) \text{ for some } b \in \mathbb{R} \setminus B\}.$$

`regsensitivity` can handle hypotheses of the form, $\beta_{\text{long}} \geq b$ for any value of b . The default hypothesis is that $\text{sign}(\beta_{\text{long}}) = \text{sign}(\beta_{\text{med}})$, where β_{med} is the coefficient on X in a regression of Y on $(1, X, W_0, W_1)$. In this case $\beta_{\text{med}} > 0$, so the default is to test the hypothesis that $\beta_{\text{long}} > 0$.

The output to `regsensitivity bounds` showed that with W_1 excluding state fixed effects, $\bar{r}_X^{\text{bp}}(.1, +\infty; (-\infty, 0]) = 1.195$. To see how this breakdown point varies with the choice of the sensitivity parameter \bar{c} , use the `breakdown` subcommand,

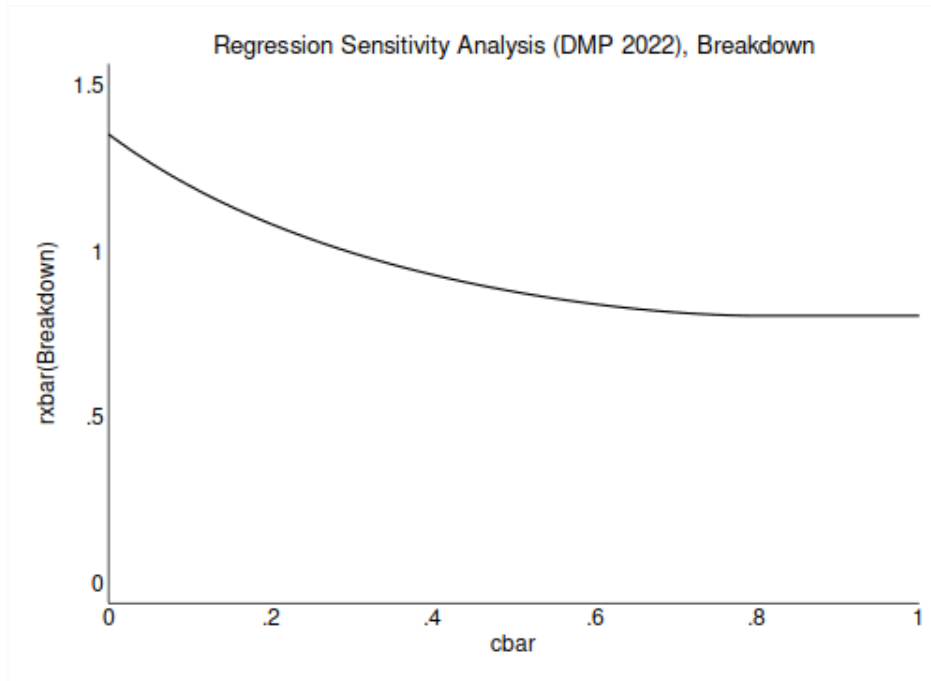
```
. regsensitivity breakdown `y' `x' `w', compare(`w1') cbar(0(.1)1)
```

| Regression Sensitivity Analysis, Breakdown Frontier | | | | | |
|---|----------------------------|-----------------|---|---------|--|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 | |
| | | Beta(short) | = | 1.925 | |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 | |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 | |
| | | R2(medium) | = | 0.105 | |
| | | Var(Y) | = | 101.739 | |
| | | Var(X) | = | 0.901 | |
| Hypothesis | : Beta > 0 | Var(X_Residual) | = | 0.882 | |
| Other Params | : rybar = +inf | | | | |

| cbar | rxbar(Breakdown) |
|-------|------------------|
| 0.000 | 135.0% |
| 0.100 | 119.5% |
| 0.200 | 108.0% |
| 0.300 | 99.3 % |
| 0.400 | 92.7 % |
| 0.500 | 87.6 % |
| 0.600 | 83.9 % |
| 0.700 | 81.4 % |
| 0.800 | 80.4 % |
| 0.900 | 80.4 % |
| 1.000 | 80.4 % |

These results can also be plotted using the `plot` subcommand:

```
. regsensitivity plot
```

To test the hypothesis that $\beta_{\text{long}} > b$ for some other value, b , specify **beta(b lb)** (lb for “lower bound”). The **beta** option can also accept a **numlist** to test a range of hypotheses. For example, the following tests the hypotheses that $\beta_{\text{long}} > b$ for a range of values of b :

```
. regsensitivity breakdown `y' `x' `w', compare(`w1') beta(-1(.2)1 lb)
```

Regression Sensitivity Analysis, Breakdown Frontier

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| Hypothesis | : Beta > Beta(Hypothesis) | Var(X_Residual) | = | 0.882 |
| Other Params | : cbar = 1, rybar = +inf | | | |

| Beta(Hypothesis) | rxbar(Breakdown) |
|------------------|------------------|
| -1.000 | 89.1 % |
| -0.800 | 87.9 % |
| -0.600 | 86.5 % |
| -0.400 | 84.8 % |
| -0.200 | 82.8 % |
| 0.000 | 80.4 % |
| 0.200 | 77.4 % |
| 0.400 | 73.8 % |
| 0.600 | 69.5 % |
| 0.800 | 64.1 % |
| 1.000 | 57.5 % |

We can also test a hypothesis of the form $\beta_{\text{long}} < b$, by specifying **beta(b ub)** (ub for “upper bound”). For example the following checks the hypothesis that $\beta_{\text{long}} < 4$:

```
. regsensitivity breakdown `y' `x' `w', compare(`w1') cbar(0(.1)1) beta(4 ub)
```

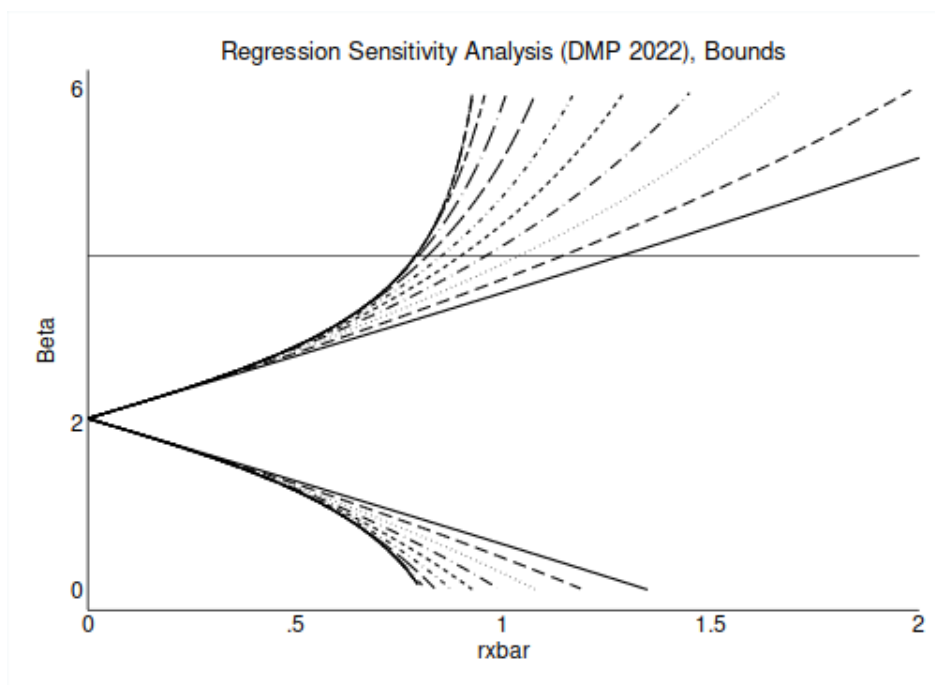
Regression Sensitivity Analysis, Breakdown Frontier

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : DMP (2022) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| Hypothesis | : Beta < 4 | Var(X_Residual) | = | 0.882 |
| Other Params | : rybar = +inf | | | |

| cbar | rxbar(Breakdown) |
|-------|------------------|
| 0.000 | 128.1% |
| 0.100 | 114.0% |
| 0.200 | 103.6% |
| 0.300 | 95.7 % |
| 0.400 | 89.6 % |
| 0.500 | 85.0 % |
| 0.600 | 81.7 % |
| 0.700 | 79.5 % |
| 0.800 | 78.8 % |
| 0.900 | 78.8 % |
| 1.000 | 78.8 % |

To see visually where the identified set intersects with 4 we can specify this alternative hypothesis in the `regsensitivity` bounds command. By including the option `beta(4 ub)` the resulting plot will include a horizontal line at 4:

```
. regsensitivity bounds `y' `x' `w', compare(`w1') rxbar(0(.2)2) cbar(0(.1)1) beta(4, ub)
. regsensitivity plot, nolegend yrange(0 6)
```



Summary statistics

The output of `regsensitivity bounds` and `regsensitivity breakdown` both include a table of summary statistics. These are as follows,

- **Number of observations**
- **Beta(short)**: The coefficient on X in the regression of Y on $(1, X)$
- **Beta(medium)**: The coefficient on X in the regression of Y on $(1, X, W_1)$
- **R2(short)**: The R-squared from the regression of Y on $(1, X)$
- **R2(medium)**: The R-squared from the regression of Y on $(1, X, W_1)$
- **Var(Y)**: Variance of Y
- **Var(X)**: Variance of X
- **Var(X_Residual)**: Variance of $X^{\perp W_1}$, the residual from the regression of X on $(1, W_1)$.

Note: For all the summary statistics reported in this table, (Y, X, W_1) are shorthand for $(Y^{\perp W_0}, X^{\perp W_0}, W_1^{\perp W_0})$ where $Y^{\perp W_0}$ is the residual from the regression of Y on $(1, W_0)$ and likewise for $X^{\perp W_0}$ and $W_1^{\perp W_0}$.

Oster 2019

This paper uses a different set of sensitivity parameters than Diegert, Masten, and Poirier (2022). These parameters are denoted by δ and R_{long}^2 . Proposition 2 in Oster (2019) gives the identified set for β_{long} as a function of these two sensitivity parameters; also see Theorem 2 in Masten and Poirier (2022). This set can be calculated for a range of sensitivity parameter values.

```
. regsensitivity bounds `y' `x' `w', compare(`w1') oster
```

Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta != 0 | Breakdown point | = | 170% |
| Other Params | : R-squared(long) = 1 | | | |

| Delta | Beta |
|--------|--------------------------|
| -0.990 | { 0.71, ., . } |
| -0.800 | { 0.93, ., . } |
| -0.600 | { 1.18, ., . } |
| -0.400 | { 1.45, ., . } |
| -0.200 | { 1.74, ., . } |
| 0.000 | { 2.05, ., . } |
| 0.200 | { 2.40, ., . } |
| 0.400 | { 2.77, ., . } |
| 0.600 | { 3.19, ., . } |
| 0.800 | { 3.66, ., . } |
| 0.990 | {-570.85, -50.04, 4.17 } |

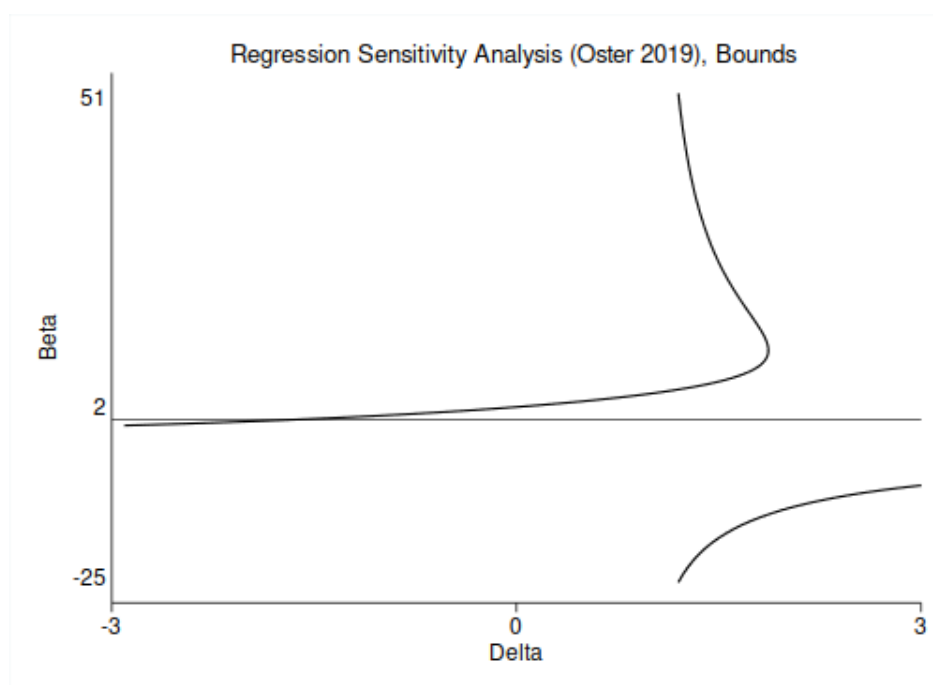
The output also shows the explain away breakdown point, which is outside the default $(-1, 1)$ range, so we'll expand the range of δ to include the breakdown point, and we'll generate a plot by including the `plot` option.

```
. regsensitivity bounds `y' `x' `w', compare(`w1') oster delta(-3(.3)3, eq) plot
```

Regression Sensitivity Analysis, Bounds

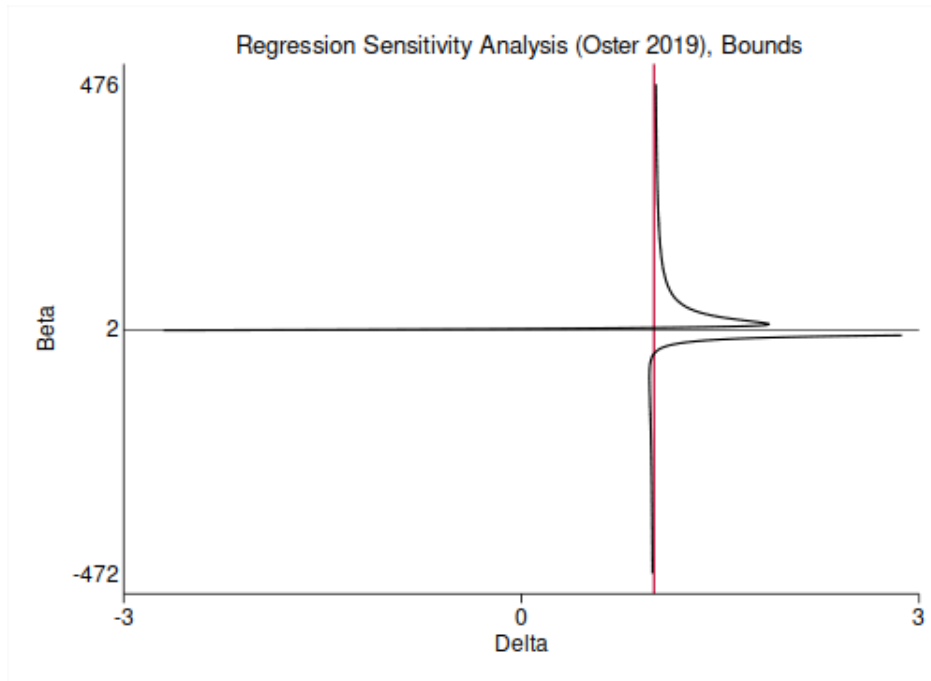
| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta != 0 | Breakdown point | = | 170% |
| Other Params | : R-squared(long) = 1 | | | |

| Delta | Beta |
|--------|------------------------|
| -3.000 | { -0.93, ., . } |
| -2.400 | { -0.54, ., . } |
| -1.800 | { -0.08, ., . } |
| -1.200 | { 0.48, ., . } |
| -0.600 | { 1.18, ., . } |
| 0.000 | { 2.05, ., . } |
| 0.600 | { 3.19, ., . } |
| 1.200 | {-25.71, 4.82, 51.71 } |
| 1.800 | {-15.46, 8.57, 14.59 } |
| 2.400 | {-12.15, ., . } |
| 3.000 | {-10.36, ., . } |



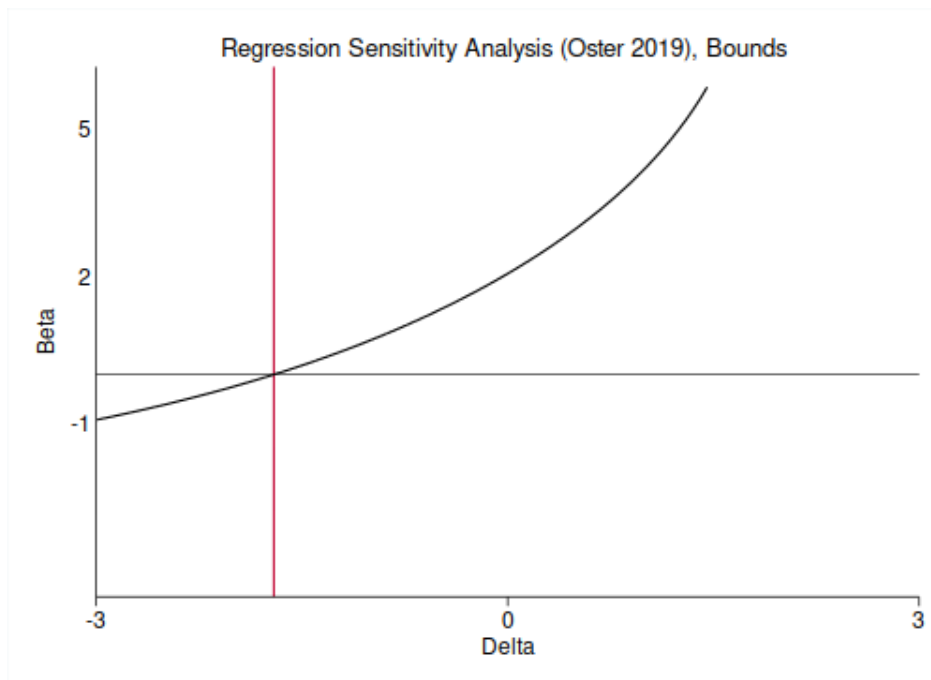
As discussed in Masten and Poirier (2022), the identified set includes arbitrarily small and large values of β_{long} around $\delta = 1$. In fact, there is an asymptote at exactly $\delta = 1$. We can expand the range of the y axis with the `ywidth` option to see this better. The `regsensitivity plot` command accepts additional *twoway options*, so we can also add a line at $\delta = 1$.

```
. regsensitivity plot, ywidth(500) xline(1)
```



On the other hand, to see that that the explain away breakdown point is in fact at -1.704 , we can narrow the range of the y-axis

```
. regsensivity plot, ywidth(4) xline(-1.704)
```



As discussed in Masten and Poirier (2022), researchers may be interested in the hypothesis that $\beta_{\text{long}} > 0$ rather than the hypothesis that $\beta_{\text{long}} \neq 0$. As in the analysis in Diegert, Masten, and Poirier (2022), we can also calculate the identified set for bounds on the absolute value of δ . That is, for a given $\bar{\delta} \geq 0$, we can

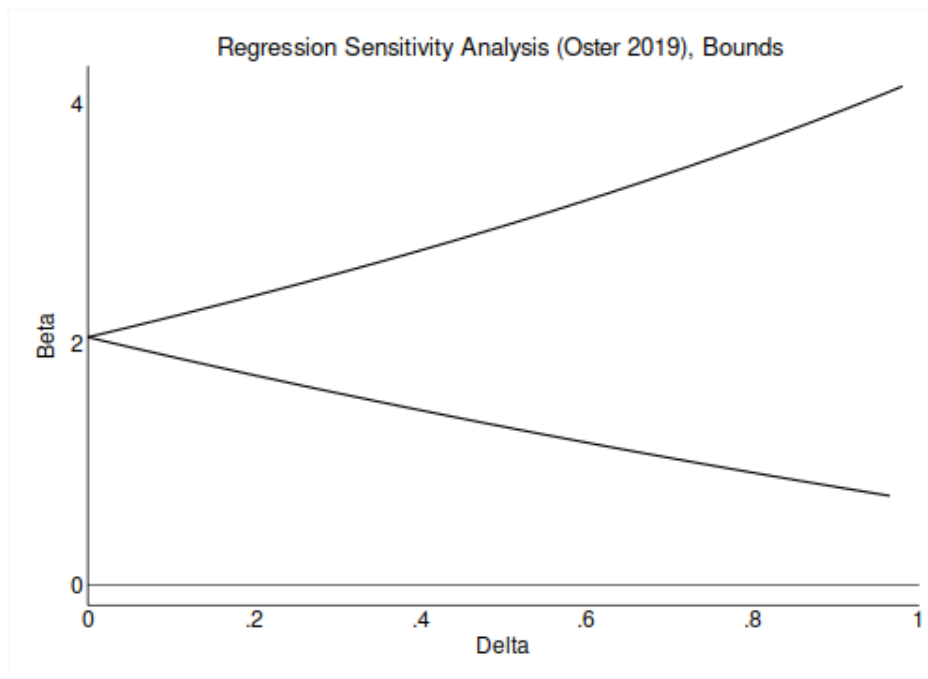
calculate the identified set of β_{long} such that $|\delta| < \bar{\delta}$. To do this, use `bound` in the `delta` option:

```
. regsensitivity bounds `y' `x' `w', compare(`w1') oster delta(0(.1).9 .999 1, bound) plot
```

Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta > 0 | Breakdown point | = | 96.5% |
| Other Params | : R-squared(long) = 1 | | | |

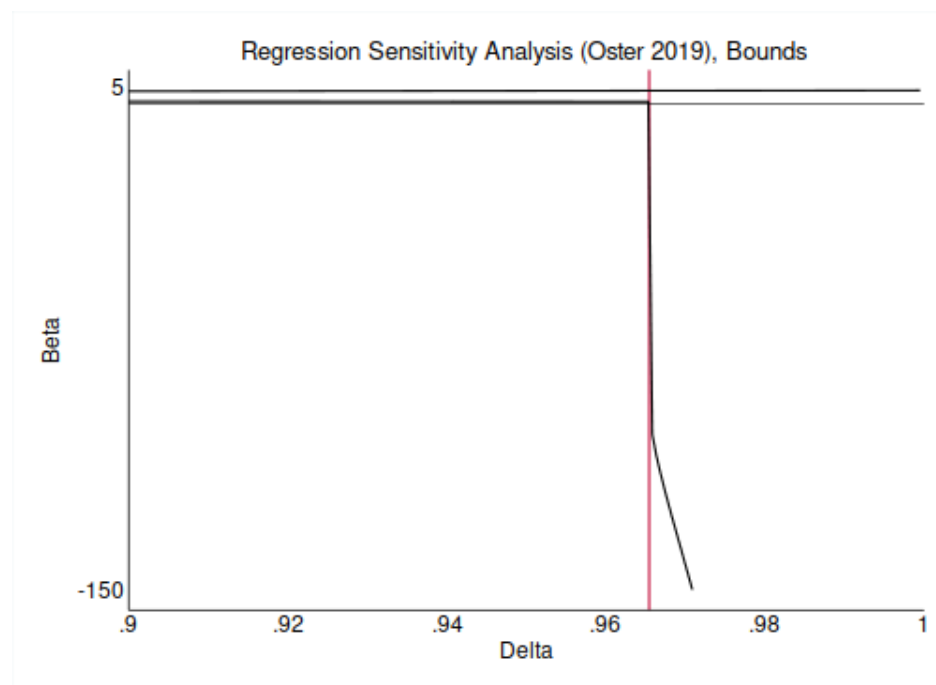
| Delta | Beta |
|-------|----------------|
| 0.000 | [2, 2] |
| 0.100 | [2, 2] |
| 0.200 | [2, 2] |
| 0.300 | [2, 3] |
| 0.400 | [1, 3] |
| 0.500 | [1, 3] |
| 0.600 | [1, 3] |
| 0.700 | [1, 3] |
| 0.800 | [1, 4] |
| 0.900 | [1, 4] |
| 0.999 | [-6,125, 4] |
| 1.000 | [-inf, +inf] |



By default, the plot sets the range of the y-axis to avoid being visually dominated by the asymptote at $\delta = 1$. In this case, we don't see where the sign change breakdown point is or where the set goes to \mathbb{R} . To see where the breakdown point is, we will plot on a more narrow range for δ and expand the range of β . The previous call to `regsensitivity bounds` stored the exact breakdown point in `e(breakdown)`; we will retrieve that

and add a vertical line at the breakdown point as well.

```
. local breakdown = e(breakdown)
. qui regssensitivity bounds `y' `x' `w', compare(`w1') oster delta(0.9(.001).99 .999 1, bound)
. regssensitivity plot, yrange(-150 5) xline(`breakdown')
```



Plotted with this wider range for β_{long} , we can see that there is a discrete jump at the estimated sign change breakdown point $\hat{\delta}^{\text{bp,sign}}(R_{\text{long}}^2) = 0.965$ and then the lower bound tends toward $-\infty$ as $\delta \rightarrow 1$.

As in Diegert, Masten, and Poirier (2022) we can also consider how breakdown points change when we change the other sensitivity parameter. The second sensitivity parameter in Oster (2019) is R_{long}^2 . To see how this affects the breakdown point use the **breakdown** subcommand with the **oster** option and pass a range of values for **r2long**. To report the explain away breakdown point, use the **beta(0 eq)** option:

```
. regssensitivity breakdown `y' `x' `w', compare(`w1') oster r2long(0(.1)1) beta(0, eq)
```

Regression Sensitivity Analysis, Breakdown Frontier

| | | | | |
|------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| Hypothesis | : Beta != 0 | Var(X_Residual) | = | 0.882 |

| R-squared(long) | Delta(Breakdown) |
|-----------------|------------------|
|-----------------|------------------|

| | |
|-------|---------|
| 0.105 | +inf |
| 0.200 | 1207.1% |
| 0.300 | 685.6% |
| 0.400 | 478.8% |
| 0.500 | 367.8% |
| 0.600 | 298.6% |
| 0.700 | 251.3% |

| | |
|-------|--------|
| 0.800 | 217.0% |
| 0.900 | 190.9% |
| 1.000 | 170.4% |

To instead consider the sign change breakdown point, specify either `beta(0 1b)` (for *lower bound*) or `beta(sign)`. This is the minimum value of $|\delta|$ such that β_{long} has the same sign as β_{med} for all $d < |\delta|$.

```
. regsensivity breakdown `y' `x' `w', compare(`w1') oster r2long(0(.1)1) beta(sign)
```

Regression Sensitivity Analysis, Breakdown Frontier

| | | | | |
|------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| Hypothesis | : Beta > 0 | Var(X_Residual) | = | 0.882 |

| R-squared(long) | Delta(Breakdown) |
|-----------------|------------------|
| 0.105 | +inf |
| 0.200 | 97.3 % |
| 0.300 | 97.3 % |
| 0.400 | 97.2 % |
| 0.500 | 97.1 % |
| 0.600 | 97.0 % |
| 0.700 | 96.9 % |
| 0.800 | 96.8 % |
| 0.900 | 96.7 % |
| 1.000 | 96.5 % |

Masten and Poirier (2022) discuss the restriction that $|\beta_{\text{med}} - \beta_{\text{long}}| < M$ for some value of M . To impose this restriction, use the option `maxovb` with `regsensivity bounds`:

```
. regsensivity bounds `y' `x' `w', compare(`w1') oster delta(0(.1)1, bound) beta(sign) maxovb(3)
```

Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|------------------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta > 0 | Breakdown point | = | 170% |
| Other Params | : R-squared(long) = 1, max OVB = 3 | | | |

| Delta | Beta |
|-------|--------------------|
| 0.000 | [2.0548, 2.0548] |
| 0.100 | [1.8939, 2.2226] |
| 0.200 | [1.7396, 2.3981] |
| 0.300 | [1.5915, 2.5819] |
| 0.400 | [1.4490, 2.7747] |
| 0.500 | [1.3120, 2.9776] |
| 0.600 | [1.1801, 3.1917] |
| 0.700 | [1.0530, 3.4184] |
| 0.800 | [0.9305, 3.6595] |
| 0.900 | [0.8124, 3.9171] |

Although this is not always the case, in this example the `maxovb` restriction is strong enough to imply that the explain away and sign change breakdown points are the same. This is because the `maxovb` restriction rules out all the negative values of β_{long} near $\delta = 1$. To see this, we plot the identified set with horizontal lines to show the magnitude bounds placed on β_{long} :

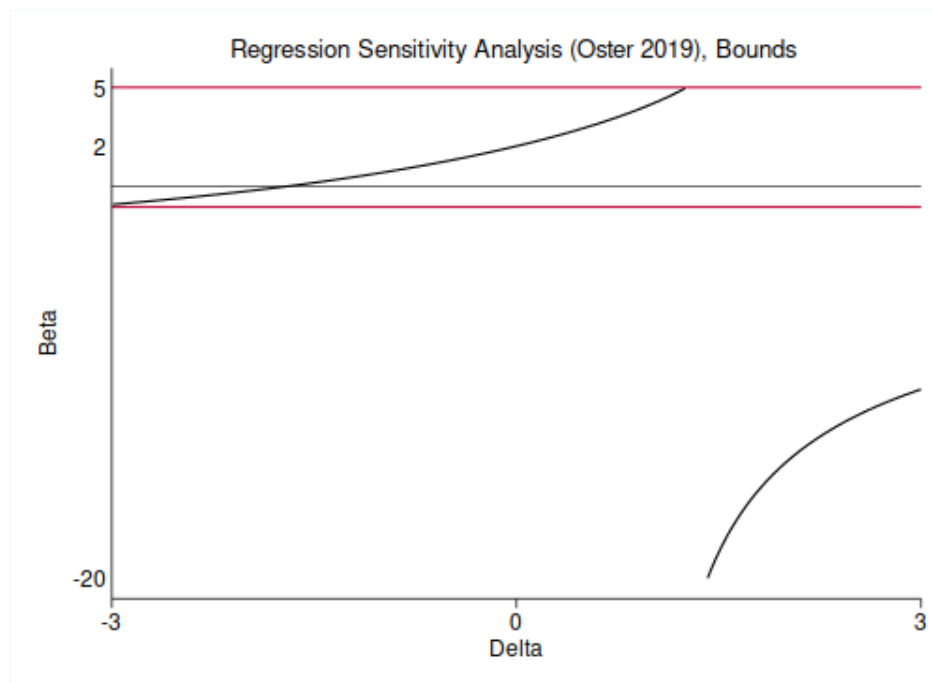
```
. regsensitivity bounds `y' `x' `w', compare(`w1') oster delta(-3(.3)3)
```

Regression Sensitivity Analysis, Bounds

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| | | Var(X_Residual) | = | 0.882 |
| Hypothesis | : Beta != 0 | Breakdown point | = | 170% |
| Other Params | : R-squared(long) = 1 | | | |

| Delta | Beta |
|--------|------------------------|
| -3.000 | { -0.93, ., . } |
| -2.400 | { -0.54, ., . } |
| -1.800 | { -0.08, ., . } |
| -1.200 | { 0.48, ., . } |
| -0.600 | { 1.18, ., . } |
| 0.000 | { 2.05, ., . } |
| 0.600 | { 3.19, ., . } |
| 1.200 | {-25.71, 4.82, 51.71 } |
| 1.800 | {-15.46, 8.57, 14.59 } |
| 2.400 | {-12.15, ., . } |
| 3.000 | {-10.36, ., . } |

```
. regsensitivity plot, yline(-1.05) yline(5.05) yrange(-20 5)
```



reg sensitivity breakdown can also accept the maxovb option:

```
. reg sensitivity breakdown `y' `x' `w', compare(`w1') oster beta(sign) r2long(0(.1)1) maxovb(22)
```

Regression Sensitivity Analysis, Breakdown Frontier

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| Hypothesis | : Beta > 0 | Var(X_Residual) | = | 0.882 |
| Other Params | : Max OVB = 22 | | | |

| R-squared(long) | Delta(Breakdown) |
|-----------------|------------------|
| 0.105 | +inf |
| 0.200 | 168.5% |
| 0.300 | 164.6% |
| 0.400 | 161.0% |
| 0.500 | 157.5% |
| 0.600 | 154.1% |
| 0.700 | 150.9% |
| 0.800 | 147.8% |
| 0.900 | 144.8% |
| 1.000 | 142.0% |

Passing a range of values of maxovb to reg sensitivity, these are displayed in the main table,

```
. reg sensitivity breakdown `y' `x' `w', compare(`w1') oster beta(sign) maxovb(2(10)100)
```

Regression Sensitivity Analysis, Breakdown Frontier

| | | | | |
|--------------|----------------------------|-----------------|---|---------|
| Analysis | : Oster (2019) | Number of obs | = | 2,036 |
| | | Beta(short) | = | 1.925 |
| Treatment | : tye_tfe890_500kNI_100_16 | Beta(medium) | = | 2.055 |
| Outcome | : avgrep2000to2016 | R2(short) | = | 0.033 |
| | | R2(medium) | = | 0.105 |
| | | Var(Y) | = | 101.739 |
| | | Var(X) | = | 0.901 |
| Hypothesis | : Beta > 0 | Var(X_Residual) | = | 0.882 |
| Other Params | : R-squared(long) = 1 | | | |

| OVB(Max) | Delta(Breakdown) |
|----------|------------------|
| 2.000 | +inf |
| 12.000 | 170.4% |
| 22.000 | 142.0% |
| 32.000 | 111.7% |
| 42.000 | 102.5% |
| 52.000 | 99.0 % |
| 62.000 | 97.5 % |
| 72.000 | 96.9 % |
| 82.000 | 96.6 % |
| 92.000 | 96.5 % |

Currently maxovb is only implemented for Oster (2019).

Finally, it is sometimes convenient to state the parameters maxovb and r2long in relative terms. When the relative suboption is specified in the r2long option, the values are relative to R_{med}^2 . For example, the input r2long(1.3, relative) is interpreted as $R_{long}^2 = 1.3R_{med}^2$. Oster (2019) suggests using this as a rule of thumb.

```
. regssensitivity bounds `y' `x' `w', compare(`w1') oster delta(-3(.3)3, eq) r2long(1.3, relative)
```

Regression Sensitivity Analysis, Bounds

```
Analysis      : Oster (2019)          Number of obs    =      2,036
                                   Beta(short)      =      1.925
Treatment     : tye_tfe890_500kNI_100_16 Beta(medium)    =      2.055
Outcome       : avgrep2000to2016      R2(short)        =      0.033
                                   R2(medium)       =      0.105
                                   Var(Y)           =     101.739
                                   Var(X)           =      0.901
                                   Var(X_Residual)   =      0.882
Hypothesis    : Beta != 0             Breakdown point  =     2329%
Other Params  : R-squared(long) = .137
```

| Delta | Beta |
|--------|------------------------|
| -3.000 | { 1.88, ., . } |
| -2.400 | { 1.92, ., . } |
| -1.800 | { 1.95, ., . } |
| -1.200 | { 1.99, ., . } |
| -0.600 | { 2.02, ., . } |
| 0.000 | { 2.05, ., . } |
| 0.600 | { 2.09, ., . } |
| 1.200 | {-31.12, 2.12, 59.83 } |
| 1.800 | {-19.06, 2.16, 24.61 } |
| 2.400 | {-15.36, 2.20, 17.57 } |
| 3.000 | {-13.37, 2.23, 14.22 } |

When the **relative** suboption is specified in the **maxovb** option, the input is interpreted relative to $|\beta_{\text{med}}|$. For example, the input **maxovb(2, relative)** is interpreted as $M = 2|\beta_{\text{med}}|$.

```
. regssensitivity bounds `y' `x' `w', compare(`w1') oster beta(sign) maxovb(2, relative)
```

Regression Sensitivity Analysis, Bounds

```
Analysis      : Oster (2019)          Number of obs    =      2,036
                                   Beta(short)      =      1.925
Treatment     : tye_tfe890_500kNI_100_16 Beta(medium)    =      2.055
Outcome       : avgrep2000to2016      R2(short)        =      0.033
                                   R2(medium)       =      0.105
                                   Var(Y)           =     101.739
                                   Var(X)           =      0.901
                                   Var(X_Residual)   =      0.882
Hypothesis    : Beta > 0             Breakdown point  =     170%
Other Params  : R-squared(long) = 1, max OVB = 4.11
```

| Delta | Beta |
|-------|--------------------|
| 0.000 | [2.0548, 2.0548] |
| 0.100 | [1.8939, 2.2226] |
| 0.200 | [1.7396, 2.3981] |
| 0.300 | [1.5915, 2.5819] |
| 0.400 | [1.4490, 2.7747] |
| 0.500 | [1.3120, 2.9776] |
| 0.600 | [1.1801, 3.1917] |
| 0.700 | [1.0530, 3.4184] |
| 0.800 | [0.9305, 3.6595] |
| 0.900 | [0.8124, 3.9171] |

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