User's Guide for `interflex`

A `STATA` Package for Producing Flexible Marginal Effect Estimates

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Description: `interflex` performs diagnostics and generates visualizations of multiplicative interaction models. Besides conventional linear interaction models, it provides two additional estimation strategies—linear regression based on pre-specified bins and locally linear regressions based on Gaussian kernel reweighting—to *flexibly* estimate the conditional marginal effect of a treatment variable on an outcome variable across different values of a moderating variable. These approaches relax the linear interaction effect assumption and safeguard against excessive extrapolation.

Citation: Jens Hainmueller, Jonathan Mummolo, and Yiqing Xu. 2016. "How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice." Available at SSRN: `https://papers.ssrn.com/abstract_id=2739221`.

This version: 1.0.1 (Comments and suggestions greatly appreciated!)

Date: March 5, 2017

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Installation

Install from SSC. You can install the package from the Boston College Statistical Software Components (SSC) archive. Simply type the following command in STATA:

```
. ssc install interflex, replace all
```

Note that sample datasets will be copied into your *current* directory.

Development Version. You can install the development version of the package by typing the following commands in STATA:

```
. cap ado uninstall interflex
. net install interflex, all replace from(http://yiqingxu.org/software/interaction/stata/)
```

Manual Installation. Manual installation takes three simple steps:

1. Download the zip file from: `http://yiqingxu.org/software/interaction/stata.zip`
2. Unzip the file
3. type the following commands in your STATA console:

```
. cap ado uninstall interflex
. net install interflex, all replace from(full_local_path)
```

Examples 1 and 2: Linear Marginal Effects

We provided four simulated samples. `sample1` is a case of a dichotomous treatment indicator with linear marginal effects; `sample2` is a case of a continuous treatment indicator with linear marginal effects; `sample3` is a case of a dichotomous treatment indicator with *nonlinear* marginal effects; and `sample4` is a case of a dichotomous treatment indicator, nonlinear marginal effects, with additive two-way fixed effects. The data generating processes (DPGs) for `sample1` and `sample2` are as follows:

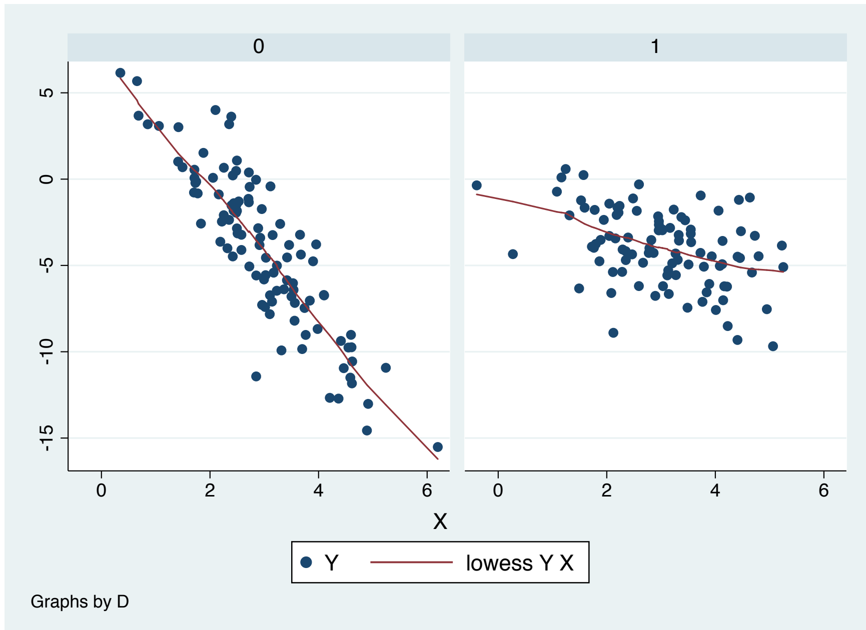
$$Y_i = 5 - 4X_i - 9D_i + 3D_iX_i + Z_i + \epsilon_i, \qquad i = 1, 2, \cdots, 200.$$

in which Y_i is the outcome for unit i, the moderator is $X_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(3,1)$, $Z_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(3,1)$, and the error term is $\epsilon_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,4)$. Both samples share the same sets of X_i, Z_i and ϵ_i, but in `sample1`, the treatment indicator is $D_i \overset{\text{i.i.d.}}{\sim} Bernoulli(0.5)$, while in `sample1` $D_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(3,1)$. The marginal effect of D on Y therefore is

$$ME_D = -9 + 3X.$$

First, we load `sample1` and draw a scatterplot. We see that the slope of Y on X in the treatment group is apparently larger (less negative) than that of the control group, suggesting a possible positive interaction between D and X. The LOESS fit also gives evidence that the relationship between X and Y differs between the two groups.

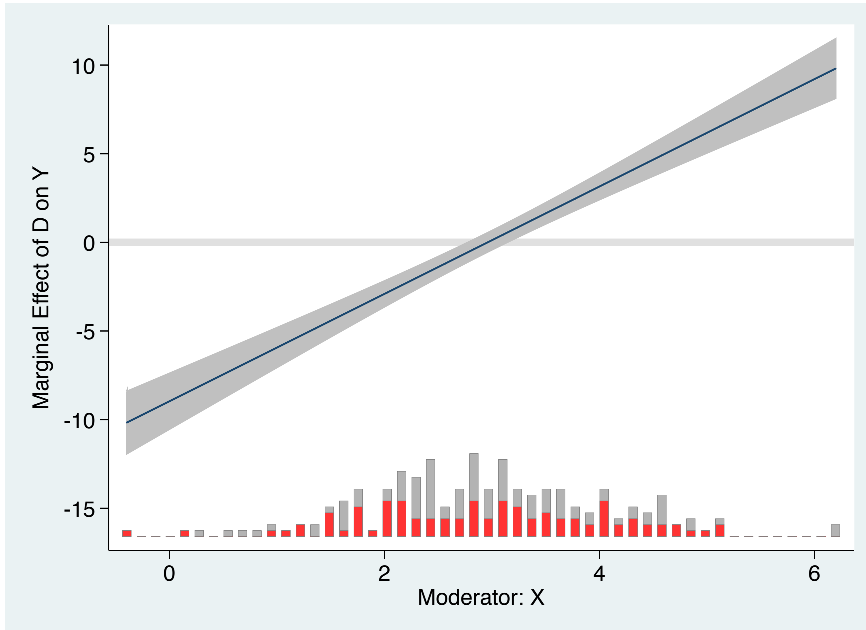
```
. use interflex_s1.dta, clear
. twoway (sc Y X) (lowess Y X), by(D)
```



`interflex` allows three estimation strategies, controlled by the `type` option. The default is `type(binning)`, which plots the linear marginal effects superimposed by the binning estimates (at low, medium, and high levels of the moderator if there are 3 bins, for instance). `type(linear)` plots the conventional linear margianl effects (Brambor, Clark, and Golder 2006). `type(kernel)` plots the marginal effects based on a kernel smoothing estimator. It produces the marginal effect estimates of the treatment on the outcome at a series of values of the moderator using kernel-weighted locally linear regressions. Variable names supplied to the program should be in the following order: (1) the outcome variable, (2) the treatment variable, (3) the moderating variable, and (4) the covariate(s).

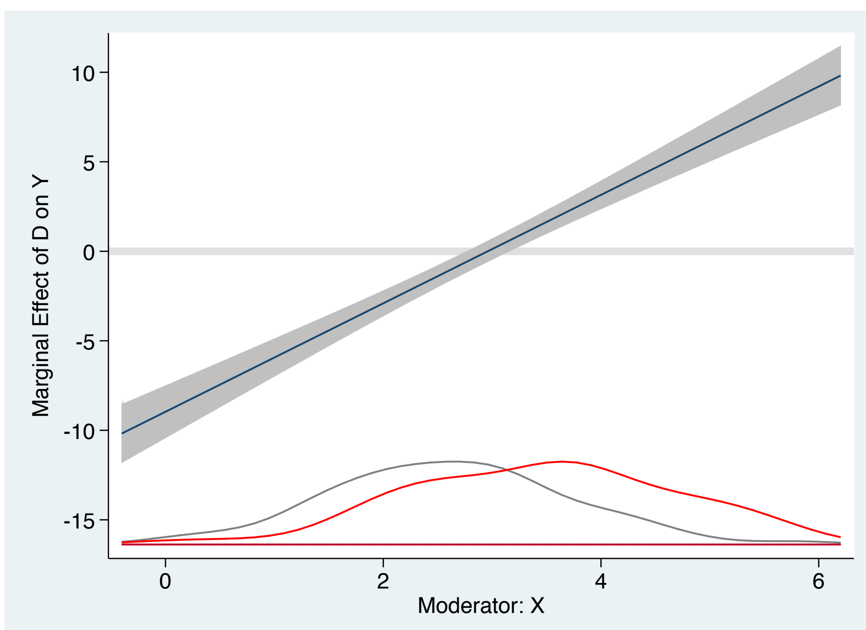
The following figure is produced with the `type(linear)` mode. The `saving` option helps store the graph with the specified *filename*; if no suffix of the *filename* is provided, the graph will be saved as a ".pdf". Notice that we display a stacked histogram at the bottom of the figure, which shows the distribution of the moderator X. In this histogram the total height of the stacked bars refers to the distribution of the moderator in the pooled sample and the red and gray shaded bars refer to the distribution of the moderator in the treatment and control groups, respectively.

```
. interflex Y D X Z1, type(linear) sav(fig1)
```



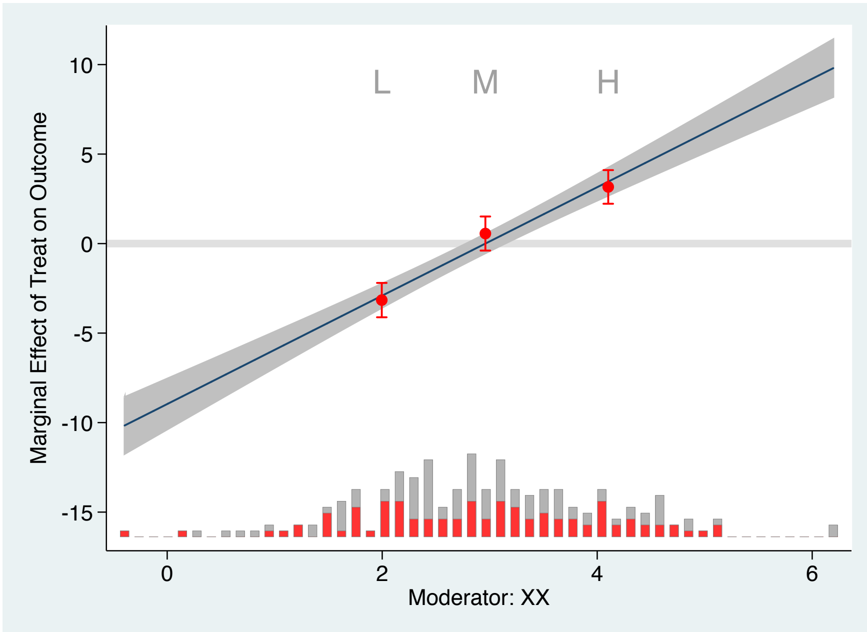
The `vce` parameter specifies the variance-covariance estimator (VC). There are five options: `homoscedastic` (default), `robust`, `cluster`, `bootstrap`, and `off` (which means no uncertainty estimates will be provided; applicable to `type(kernel)` only). We also allow users to use density plots, instead of histograms, to visualize the distributions of the moderator of the two groups.

```
. interflex Y D X Z1, type(linear) vce(robust) xd(density)
```



As mentioned above, the default estimation strategy is the binning approach. Below we change the VCE to `robust` and specify labels for the key variables. We see that the Wald test cannot reject the NULL hypothesis that the linear interaction model and the three-bin model are statistically equivalent (p = 0.51).

```
. interflex Y D X Z1, vce(r) ylab(Outcome) dlab(Treat) xlab(XX)
p value of Wald test: 0.5085
```



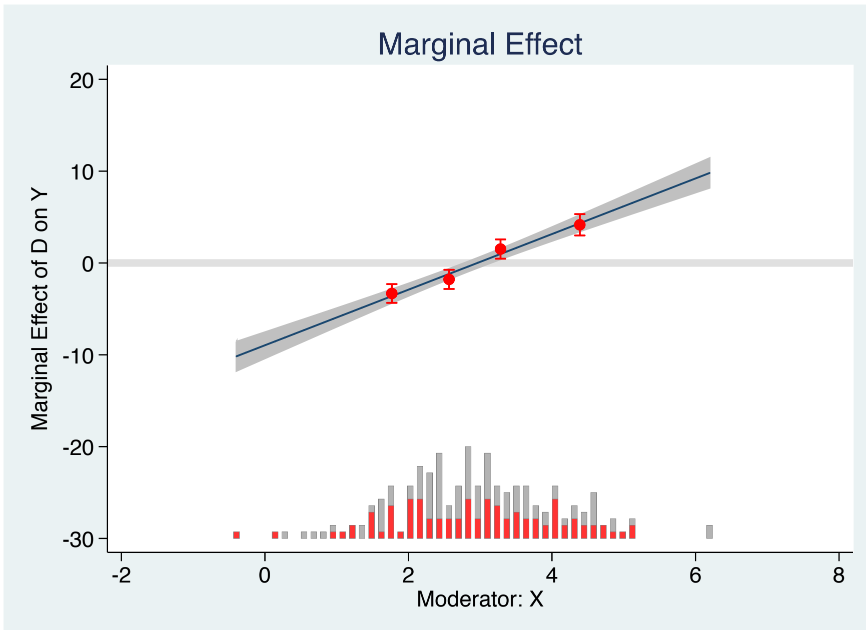
`interflex` stores the binning estimates, as well as the (linear) marginal effect estimates.

```
. return list
scalars:
              r(pwald) =  .5085297236396487
matrices:
             r(estBin) :  3 x 5
            r(margeff) :  50 x 5
. mat list r(estBin)

r(estBin)[3,5]
            x0    bin_marg      bin_se    bin_CI_l    bin_CI_u
r1   1.9960205  -3.1572332   .48940802  -4.1164553  -2.1980111
r2   2.9597931   .56089646   .48592494  -.39149892   1.5132919
r3   4.1024646   3.1646607    .4796252   2.2246126   4.1047088

. mat list r(margeff)

r(margeff)[50,5]
         xlevel         marg           se         CI_l         CI_u
 r1  -.39606353   -10.163198     .8087585   -11.748335   -8.5780604
 r2  -.26153364   -9.7557915    .77931748   -11.283226   -8.2283573
 r3  -.12700375    -9.348385    .75003179    -10.81842   -7.8783497
 r4   .00752614   -8.9409786    .72092035   -10.353956   -7.5280006
 r5   .14205604   -8.5335721    .69200517   -9.8898773   -7.1772669
```

r6	.27658593	-8.1261656	.66331191	-9.4262331	-6.8260982
r7	.41111582	-7.7187592	.63487065	-8.9630828	-6.4744356
r8	.54564571	-7.3113527	.60671684	-8.5004959	-6.1222096
r9	.68017561	-6.9039463	.57889243	-8.0385546	-5.7693379
r10	.8147055	-6.4965398	.55144726	-7.5773566	-5.415723
r11	.94923539	-6.0891333	.5244409	-7.1170186	-5.0612481
r12	1.0837653	-5.6817269	.49794473	-6.6576806	-4.7057731
r13	1.2182952	-5.2743204	.47204468	-6.199511	-4.3491298
r14	1.3528251	-4.8669139	.44684442	-5.7427129	-3.991115
r15	1.487355	-4.4595075	.42246919	-5.2875319	-3.6314831
r16	1.6218849	-4.052101	.3990702	-4.8342642	-3.2699378
r17	1.7564147	-3.6446946	.37682936	-4.3832665	-2.9061226
r18	1.8909446	-3.2372881	.35596381	-3.9349643	-2.5396119
r19	2.0254745	-2.8298816	.33672931	-3.4898589	-2.1699043
r20	2.1600044	-2.4224752	.31942065	-3.0485281	-1.7964222
r21	2.2945343	-2.0150687	.30436655	-2.6116162	-1.4185212
r22	2.4290642	-1.6076622	.29191605	-2.1798072	-1.0355173
r23	2.5635941	-1.2002558	.28241368	-1.7537764	-.64673515
r24	2.698124	-.79284932	.27616394	-1.3341207	-.25157795
r25	2.8326539	-.38544286	.27338998	-.92127737	.15039166
r26	2.9671838	.02196361	.27419732	-.51545327	.55938049
r27	3.1017137	.42937007	.27855483	-.11658736	.9753275
r28	3.2362436	.83677653	.28630043	.27563799	1.3979151
r29	3.3707735	1.244183	.29716933	.6617418	1.8266242
r30	3.5053033	1.6515895	.31083406	1.0423659	2.260813
r31	3.6398332	2.0589959	.32694426	1.418197	2.6997949
r32	3.7743631	2.4664024	.34515765	1.7899058	3.142899
r33	3.908893	2.8738088	.36515968	2.158109	3.5895087
r34	4.0434229	3.2812153	.38667287	2.5233504	4.0390802
r35	4.1779528	3.6886218	.4094591	2.8860967	4.4911468
r36	4.3124827	4.0960282	.43331758	3.2467414	4.9453151
r37	4.4470126	4.5034347	.4580808	3.6056128	5.4012566
r38	4.5815425	4.9108412	.48360981	3.9629833	5.858699
r39	4.7160724	5.3182476	.50978957	4.3190784	6.3174168
r40	4.8506023	5.7256541	.53652482	4.6740847	6.7772234
r41	4.9851322	6.1330605	.56373655	5.0281572	7.2379639
r42	5.1196621	6.540467	.59135898	5.3814247	7.6995093
r43	5.254192	6.9478735	.61933715	5.733995	8.161752
r44	5.3887218	7.3552799	.64762497	6.0859583	8.6246015
r45	5.5232517	7.7626864	.67618357	6.4373909	9.0879818
r46	5.6577816	8.1700929	.70498005	6.7883573	9.5518284
r47	5.7923115	8.5774993	.73398641	7.1389124	10.016086
r48	5.9268414	8.9849058	.76317872	7.489103	10.480709
r49	6.0613713	9.3923122	.79253643	7.8389694	10.945655
r50	6.1959012	9.7997187	.82204183	8.1885463	11.410891

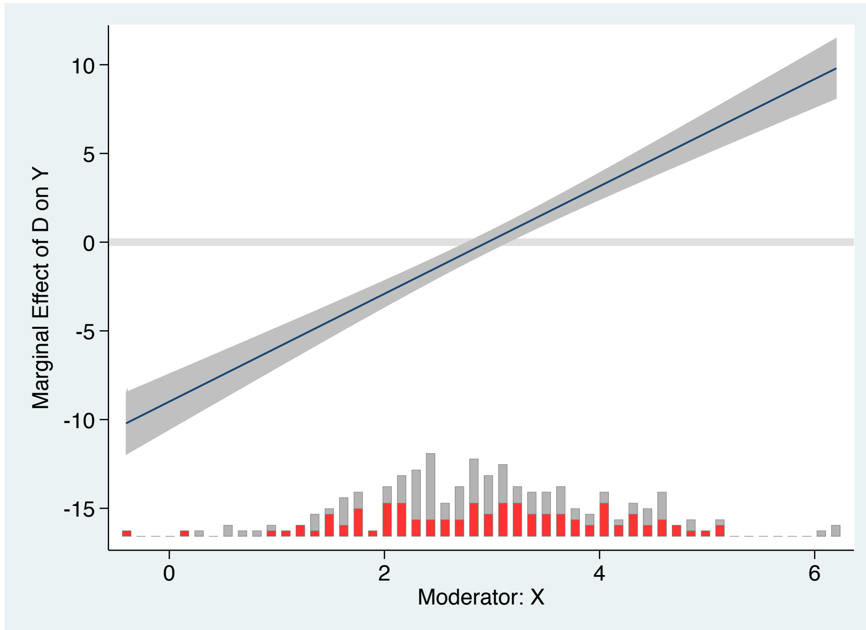
We can also change the number of bins using nbins (each bin would have roughly the same number of observations), add a title using title, and control x- and y-axes ranges using xrange and yrange.

```
. interflex Y D X Z1, vce(r) n(4) ti(Marginal Effect) xr(-2 8) yr(-30 20)
p value of Wald test: 0.6220
```



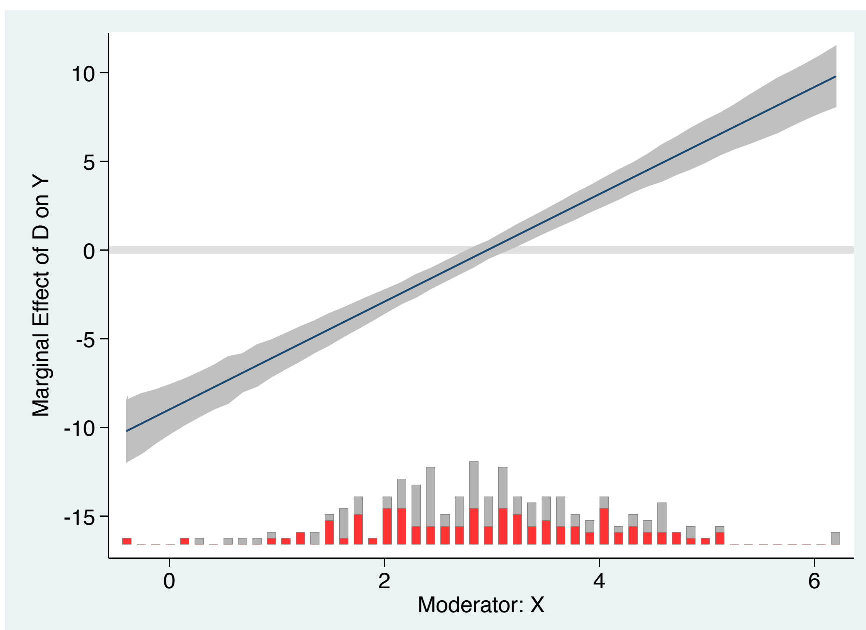
The third estimation strategy is the kernel approach, which allows the marginal effects to be fully flexible. The optimal bandwidth is automatically selected via cross-validation. When the linear interaction effect assumption is correct, the result converges to that using the linear approach. The optimal bandwidth (5.7) is relatively large.

```
. interflex Y D X Z1, type(kernel)
Cross-validating bandwidth...
The optimal bandwidth is    5.6750
```



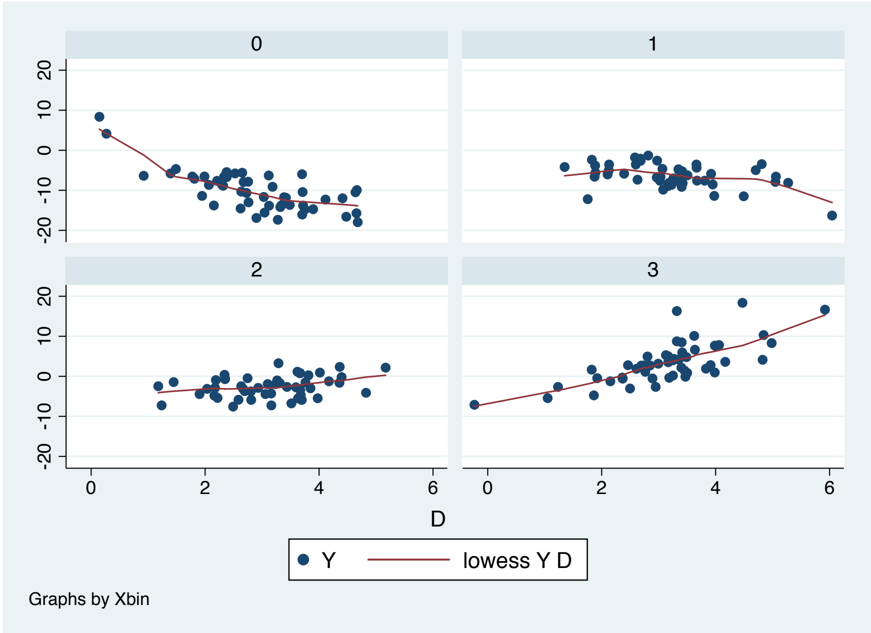
Cross-validation usually takes some time. As an alternative, users can manually specify a bandwidth using the `bw` option. We can also tell the program to produce bootstrap confidence intervals by using `vce(bootstrap)` and specify the number of bootstrap runs using the `reps` option.

```
. interflex Y D X Z1, type(kernel) bw(5.6) vce(boot) reps(200)
```



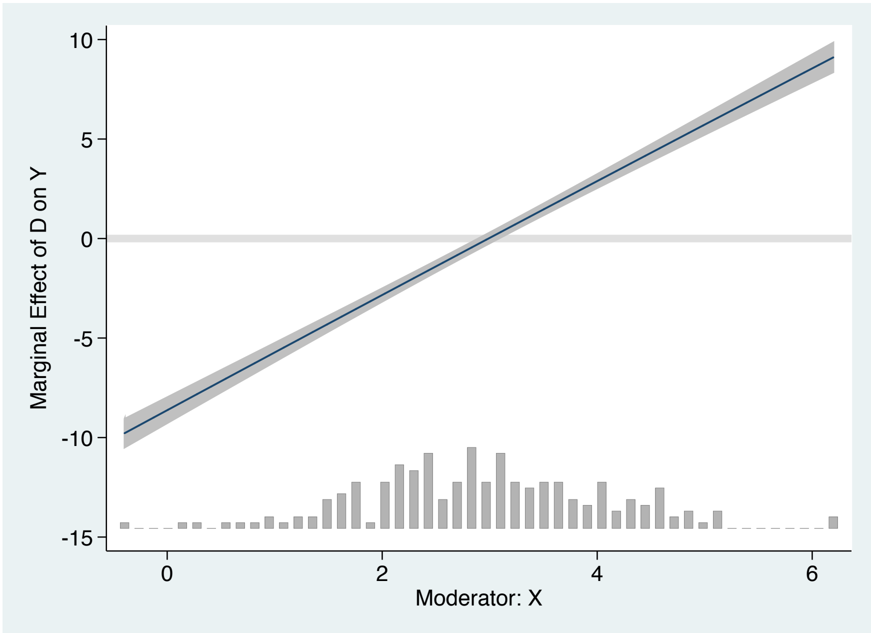
`sample2` is a case with a continuous treatment indicator. First, we plot the raw data by subsetting the sample based on the value of the moderator X. We see that the slope of D on Y gradually increases as X becomes larger, indicating a positive interaction effect.

```
. use interflex_s2.dta, clear
. egen Xbin = cut(X), group(4)
. twoway (sc Y D) (lowess Y D), by(Xbin)
```



Again, the kernel estimator recovers the linear marginal effect of D on Y across different values of X (bandwidth selected via cross-validation).

```
. interflex Y D X Z1, type(kernel) bw(5.7)
```



Example 3: Nonlinear Marginal Effects

The third example (`sample3`) is a case with a nonlinear marginal effect. The DGP is as follows:

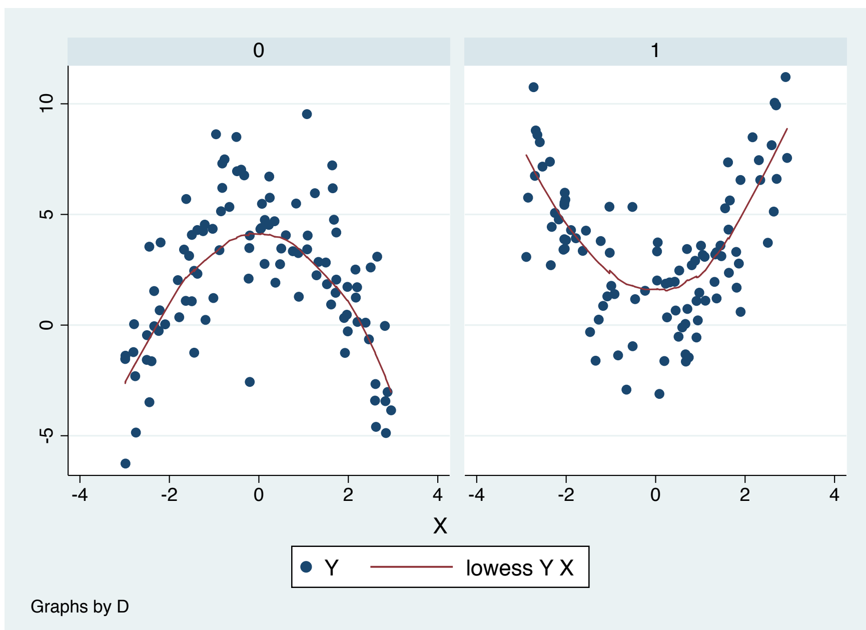
$$Y_i = 2.5 - X_i^2 - 5D_i + 2D_iX_i^2 + Z_i + \varepsilon_i, \qquad i = 1, 2, \cdots, 200.$$

Y_i is the outcome, the moderator is $X_i \overset{\text{i.i.d.}}{\sim} \mathcal{U}(-3, 3)$, the treatment indicator is $D_i \overset{\text{i.i.d.}}{\sim} Bernoulli(0.5)$, one covariate is $Z_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(3, 1)$, and the error term is $\varepsilon_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, 4)$. The marginal effect of D on Y therefore is

$$ME_D = -5 + 2X^2.$$

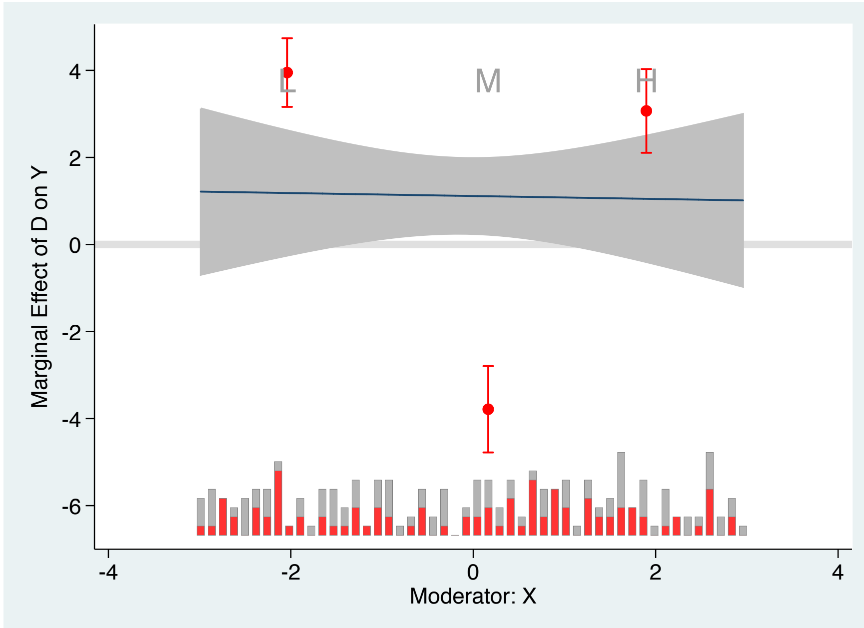
As usual, first we break the sample into two groups based on treatment status. In each group, we observe distinctive and nonlinear relationships between X and Y

```
. use interflex_s3.dta, clear
. twoway (sc Y X) (lowess Y X), by(D)
```



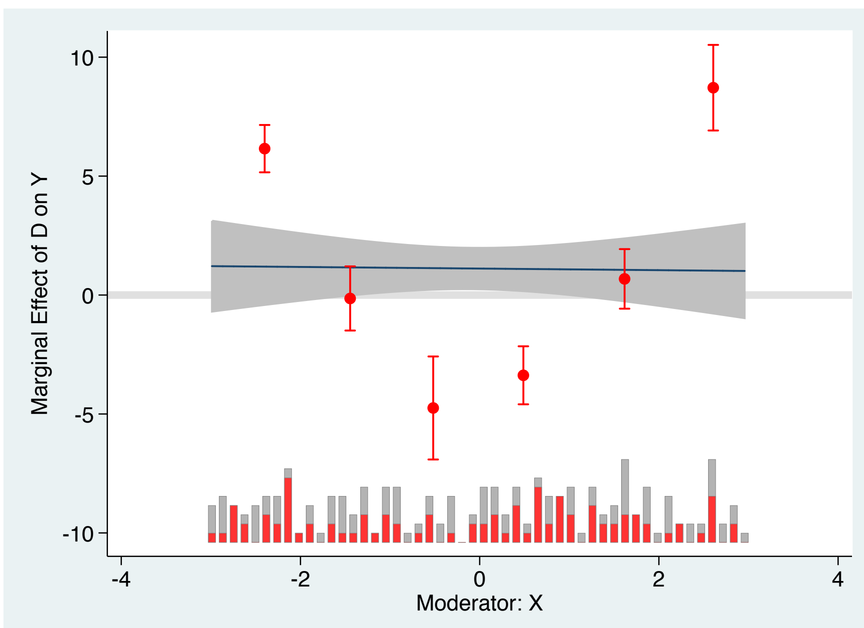
The binning approach also reveals that the marginal effect is nonlinear. Clearly, we wouldn't be able to recover this fact using the traditional linear marginal effect approach. The p-value of the Wald statistic is 0.0000, safely rejecting the NULL hypothesis that the linear interaction model and the three-bin model are statistically equivalent.

```
. interflex Y D X Z1, vce(r)
p value of Wald test: 0.0000
```



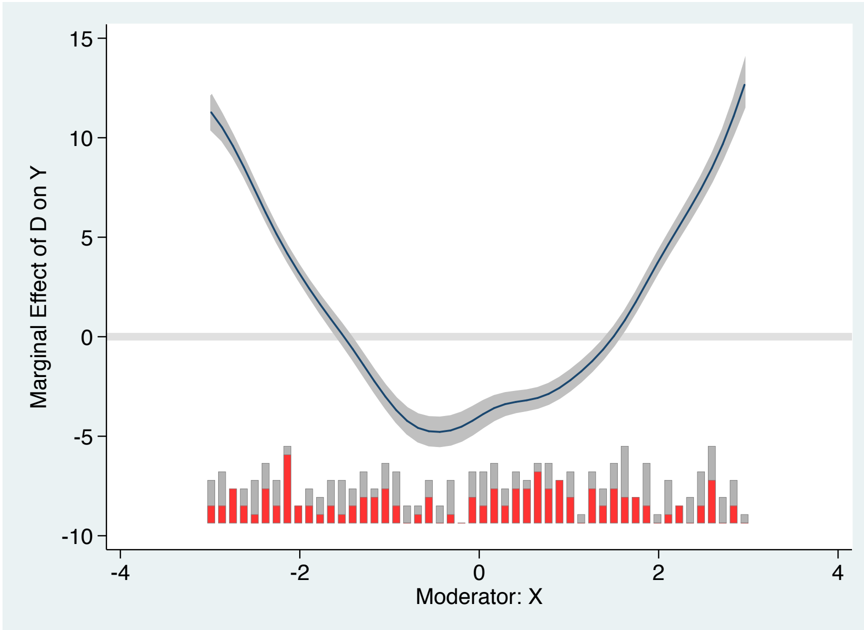
Users can specify bin cutoffs using the cutoffs option. Five cutoff values result in six bins.

```
. interflex Y D X Z1, vce(r) cut(-2 -1 0 1 2)
p value of Wald test: 0.0000
```



Once again, the kernel estimator recovers the nonlinear marginal effects that are very close to those implied by the true DGP.

```
. interflex Y D X Z1, type(kernel)
Cross-validating bandwidth...
The optimal bandwidth is    0.3453
```



`interflex` stores the bandwidth, results from the cross-validation procedure (if conducted), as well as the marginal effect estimates.

```
. return list
scalars:
           r(bandwidth) =  .3452949281898731
matrices:
              r(CVout) :  20 x 2
            r(margeff) :  50 x 5
. mat list r(CVout)
r(CVout)[20,2]
            bw       MSPE
 r1  .29726152  19.710854
 r2  .34529493  19.707344
 r3  .40108988  19.821578
 r4  .46590052  20.044265
 r5  .54118369  20.384937
 r6  .62863159  20.886985
 r7  .73020987  21.635067
 r8  .84820182  22.728136
 r9  .98525965  24.245804
r10  1.1444642  26.282206
r11  1.3293939  28.919365
r12  1.5442059  32.031695
r13  1.7937285  35.285973
r14  2.0835705  38.364342
r15   2.420247  41.081345
r16  2.8113259  43.369511
r17  3.2655978  45.234116
```

```
r18   3.7932738   46.717565
r19   4.4062151   47.876913
r20   5.1181993   48.770929
```

Example 4: Nonlinear Marginal Effects with Fixed Effects

Finally, we move on to models with additive fixed effects. The DGP of `sample4` is as follows:

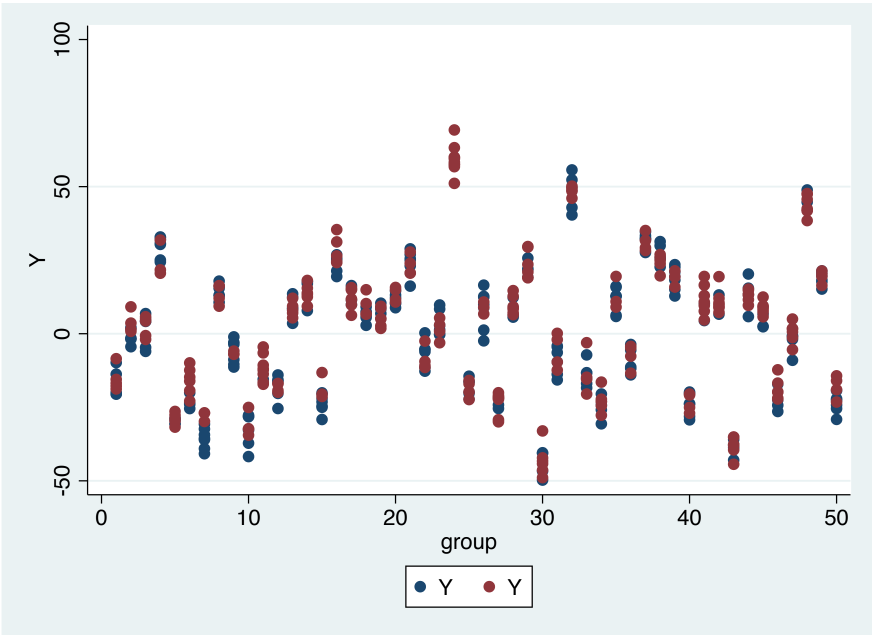
$$Y_{it} = 2.5 - X_{it}^2 - 5D_{it} + 2D_{it}X_{it}^2 + Z_{it} + \alpha_i + \xi_t + \varepsilon_{it}, \qquad i = 1, 2, \cdots, 500.$$

in which $X_{it} \overset{\text{i.i.d.}}{\sim} \mathcal{U}(-3,3)$, $D_{it} \overset{\text{i.i.d.}}{\sim} Bernoulli(0.5)$, $Z_{it} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(3,1)$, $\varepsilon_{it} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,4)$, $\alpha_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,400)$ and $\xi_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,1)$. The marginal effect of D on Y therefore is the same as in `sample3`:

$$ME_D = -5 + 2X^2.$$

It is obvious that a large chunk of the variation in the outcome variable is driven by group fixed effects α_i. Below is a scatterplot of the raw data (group index vs. outcome). Red and blue dots represent treatment and control units, respectively. We can see that outcomes are highly correlated within a group.

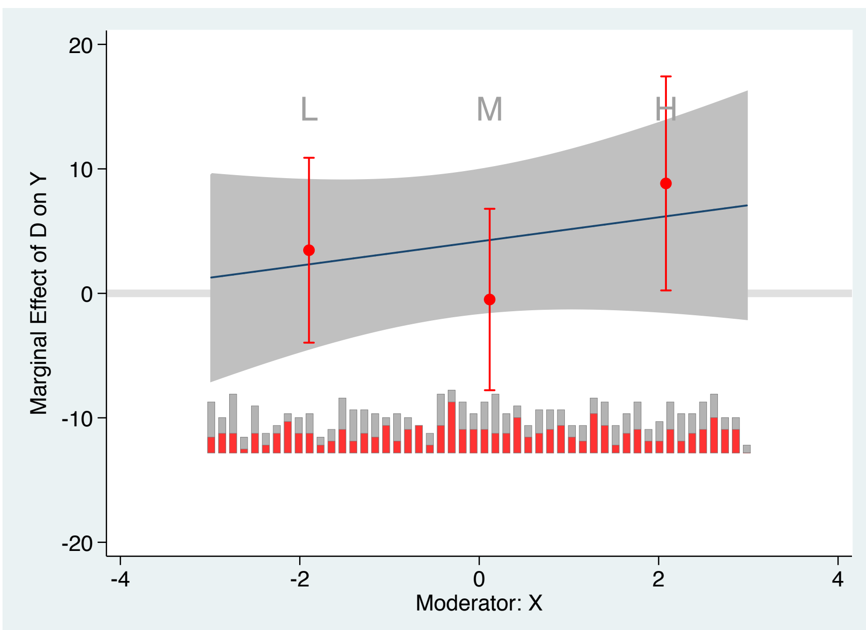
```
. use interflex_s4.dta, clear
. twoway (sc Y group if D==0) (sc Y group if D==1)
```



When fixed effects are present, it is possible that we cannot observe a clear pattern of marginal effects in the raw plot as before, while binning estimates have wide confidence intervals (note that the standard errors are clustered at the `group` level):

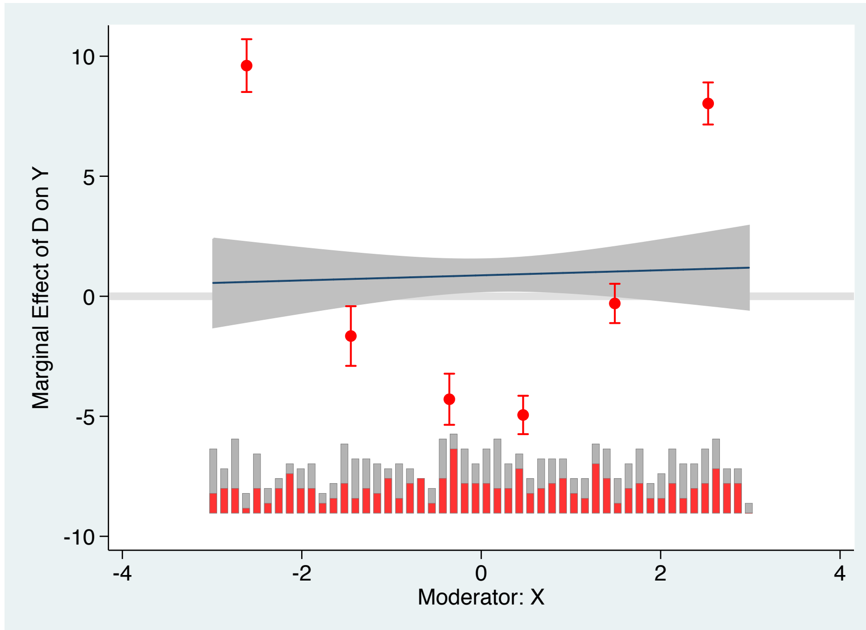
```
. twoway (sc Y X) (lowess Y X), by(D)
```


```
. interflex Y D X Z1, cl(group)
p value of Wald test: 0.0452
```



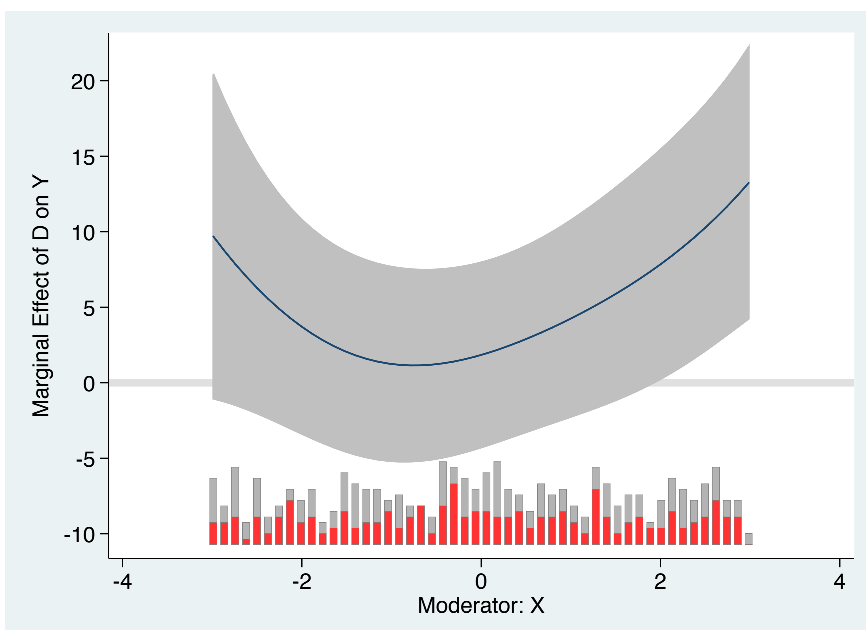
The binning estimates are much more informative when fixed effects are included, by using the `fe` option. Note that the number of group indicators can exceed 2.

```
. interflex Y D X Z1, fe(group year) cl(group) cut(-2 -1 0 1 2)
p value of Wald test: 0.0000
```



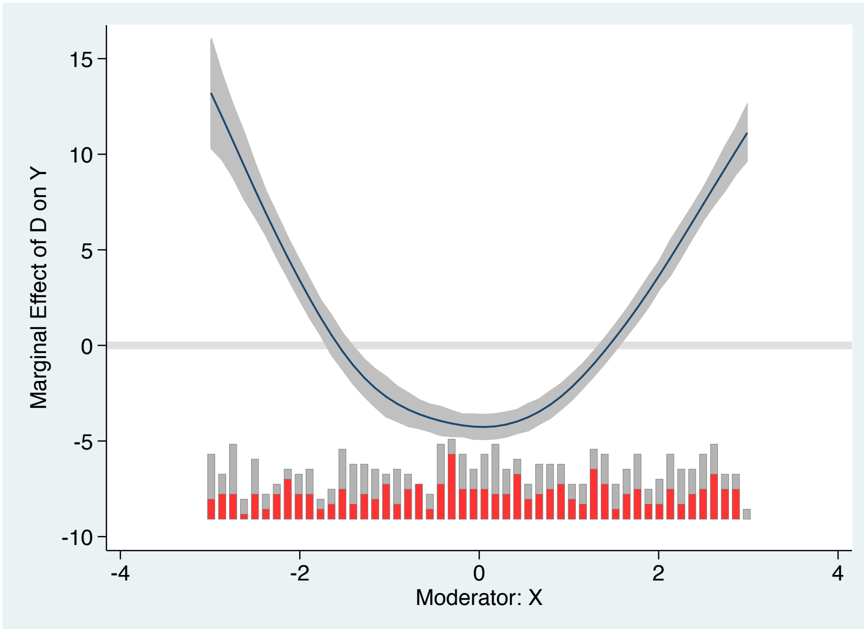
When fixed effects are not taken into account, the kernel estimates are also less precisely estimated. Because the model is incorrectly specified, cross-validated bandwidths also tend to be bigger than optimal.

```
. interflex Y D X Z1, type(kernel) cl(group)
Cross-validating bandwidth...
The optimal bandwidth is    1.3367
```



Controlling for fixed effects by using the `fe` option solves this problem. The estimates are now much closer to the population truth. Note that, when both `cl` and `vce(boot)` options are supplied, a block bootstrap procedure will be performed.

```
. interflex Y D X Z1, type(kernel) fe(group year) cl(group) vce(boot) reps(200)
Cross-validating bandwidth...
The optimal bandwidth is    0.5971
```



With large datasets, cross-validation or bootstrapping can take a while. One way to check the result quickly is not to produce the uncertainty estimates (using `vce(off)`). `interflex` will then present the point estimates only. Another way is to supply a reasonable bandwidth manually by using the bw option such that cross-validation will be skipped. [**Note:** our `R` program is much faster by taking advantage of optimized `C++` code and using parallel computing.]

```
. interflex Y D X Z1, type(kernel) fe(group year) cl(group) vce(off) yr(-10 15) bw(0.60)
```