Stata Webinar

Introduction to lasso using Stata

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Outline

- Overview of lasso in Stata

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- Lasso for prediction and model selection
    - Motivation and basic theoretical aspects
    - Example for a linear model
        - Basic workflow
        - Some tools and options

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- "Lasso was an acronym for 'least absolute shrinkage and selection operator'. Today, lasso is considered a word"

Lasso for prediction and model selection

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- If data have lots of covariates, which ones should we include in our prediction model?

Using penalized regression to avoid overfitting

- Problems if all potential covariates would be included:
  - It would not be possible if $p > N$
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- A way to avoid overfitting is by penalizing the objective function

$$Q = \frac{1}{N}\sum_{i=1}^{N} w_i f(y_i, \beta_0 + \mathbf{x}_i\beta')$$

- $f(.)$ is a measure of prediction error

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- $f(.)$ is a measure of prediction error
- How does lasso penalize the objective function?

Using penalized regression to avoid over-fitting

Lasso (Tibshirani, 1996) minimizes the penalized objective function

$$Q_L = \frac{1}{N}\sum_{i=1}^{N} w_i f(y_i, \beta_0 + \mathbf{x}_i\boldsymbol{\beta}') + \lambda \sum_{j=1}^{p} k_j|\beta_j|$$

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- Least absolute shrinkage and selection operator (lasso)

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- Penalized objective function for lasso

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- Penalized objective function for square-root lasso

$$Q_L = \sqrt{\frac{1}{N}\sum_{i=1}^{N} w_i(y_i - \beta_0 - \mathbf{x}_i\boldsymbol{\beta}')^2} + \frac{\lambda}{N}\sum_{j=1}^{p} k_j|\beta_j|$$

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5. steps 3 and 4 are repeated for each fold
6. the prediction errors are then averaged over all folds
7. steps 3, 4, 5 and 6 are repeated for each λ in the grid
8. select the $\lambda*$ with the smallest average prediction error, and refit lasso using $\lambda*$ on the original data

Example on lasso for prediction with a linear model

- Predicting infant birth weight

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- Basic covariates: 5 binary variables and 6 continuous variables of mothers and fathers
- Covariates: main effects and interactions (117 covariates)

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- Basic covariates: 5 binary variables and 6 continuous variables of mothers and fathers
- Covariates: main effects and interactions (117 covariates)
- Number of observations: 4642
- Among OLS, lasso, elastic-net, and square-root lasso, which method should be used to predict the infant birth weight?

Workflow

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  - Evaluate lasso predictions on a sub-sample that we did not use to fit the lasso. So, we randomly split data into training and testing sample

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 . use cattaneo2
(Excerpt from Cattaneo (2010) Journal of Econometrics 155: 138154)
. set seed 1907
. splitsample, generate(sample) split(0.70 0.30)
. label define lbsample 1 "Training" 2 "Testing"
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- Step 2: Create macro with factor variable syntax

```
 . global covs (c.mage c.fage c.mage c.fage c.monthslb)##(c.mage ///
>       c.fage c.mage c.fage c.monthslb) (mmarried mhisp fhisp ///
>           foreign alcohol msmoke fbaby prenatal1)##(c.mage c.fage ///
>           c.medu c.fedu c.monthslb)
```

Workflow

- Step 3: Select λ parameter value using training sample

```
. quietly regress bweight $covs if sample == 1
. estimates store ols
. quietly lasso linear bweight $covs if sample == 1
. estimates store lasso
. quietly elasticnet linear bweight $covs if sample == 1, alpha(0.2 0.5 0.75 0.9)
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- By default, λ is chosen by 10-fold cross-validation (grid of 100 values of λ)
- **`estimates store`** stores estimation results
- In **`elasticnet`**, option **`alpha()`** specifies some α values for the penalty term

Workflow

- Step 4: Evaluate prediction performance using testing sample

```
. lassogof ols lasso elastnet sqlasso, over(sample)
Penalized coefficients
```

Name	sample	MSE	R-squared	Obs
ols				
	Training	304368.1	0.0800	3,249
	Testing	328554.5	0.0463	1,393
lasso				
	Training	310573.1	0.0613	3,249
	Testing	324874.6	0.0570	1,393
elastnet				
	Training	310358.5	0.0619	3,249
	Testing	324727.4	0.0574	1,393
sqlasso				
	Training	310176.3	0.0625	3,249
	Testing	324962.4	0.0567	1,393

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sqlasso				
	Training	310176.3	0.0625	3,249
	Testing	324962.4	0.0567	1,393

- Elastic-net is the best method (lowest MSE in the testing sample)

Workflow

- Step 5: Compute predictions using the best estimator

```
. quietly elasticnet linear bweight $covs, alpha(0.2 0.5 0.75 0.9)
. estimates store elastnetfull
. use cattaneo2_new, clear
(New data)
. estimates restore elastnetfull
(results elastnetfull are active now)
. predict yhat_pen
(options xb penalized assumed; linear prediction with penalized coefficients)
. predict yhat_postsel, postselection
(option xb assumed; linear prediction with postselection coefficients)
```

Workflow

- Step 5: Compute predictions using the best estimator

```
. quietly elasticnet linear bweight $covs, alpha(0.2 0.5 0.75 0.9)
. estimates store elastnetfull
. use cattaneo2_new, clear
(New data)
. estimates restore elastnetfull
(results elastnetfull are active now)
. predict yhat_pen
(options xb penalized assumed; linear prediction with penalized coefficients)
. predict yhat_postsel, postselection
(option xb assumed; linear prediction with postselection coefficients)
```

  - By default, **`predict`** uses the penalized coefficients

Workflow

- Step 5: Compute predictions using the best estimator

```
. quietly elasticnet linear bweight $covs, alpha(0.2 0.5 0.75 0.9)
. estimates store elastnetfull
. use cattaneo2_new, clear
(New data)
. estimates restore elastnetfull
(results elastnetfull are active now)
. predict yhat_pen
(options xb penalized assumed; linear prediction with penalized coefficients)
. predict yhat_postsel, postselection
(option xb assumed; linear prediction with postselection coefficients)
```

  - By default, **predict** uses the penalized coefficients
  - The **postselection** option uses post-selection coefficients (OLS on variables selected by **elasticnet**). They are expected to perform better in out-of-sample prediction than the penalized coefficients

Display **lasso** output

```
. estimates restore lasso
(results lasso are active now)

. lasso

Lasso linear model                          No. of obs         =      3,249
                                            No. of covariates  =        117
Selection: Cross-validation                 No. of CV folds    =         10

--------------------------------------------------------------------------
         |                                No. of      Out-of-      CV mean
         |                               nonzero       sample   prediction
      ID |     Description      lambda     coef.    R-squared        error
---------+----------------------------------------------------------------
       1 |    first lambda     115.008         0       0.0003     330748.1
      26 |   lambda before    11.23639        17       0.0514     313825.7
    * 27 | selected lambda    10.23818        17       0.0515     313799.9
      28 |    lambda after     9.32865        19       0.0515     313823.9
      39 |     last lambda    3.352543        28       0.0501     314281.9
--------------------------------------------------------------------------
* lambda selected by cross-validation.
```

Display `lasso` output

```
. estimates restore lasso
(results lasso are active now)
. lasso
Lasso linear model                          No. of obs        =      3,249
                                            No. of covariates =        117
Selection: Cross-validation                 No. of CV folds   =         10
```

ID	Description	lambda	No. of nonzero coef.	Out-of-sample R-squared	CV mean prediction error
1	first lambda	115.008	0	0.0003	330748.1
26	lambda before	11.23639	17	0.0514	313825.7
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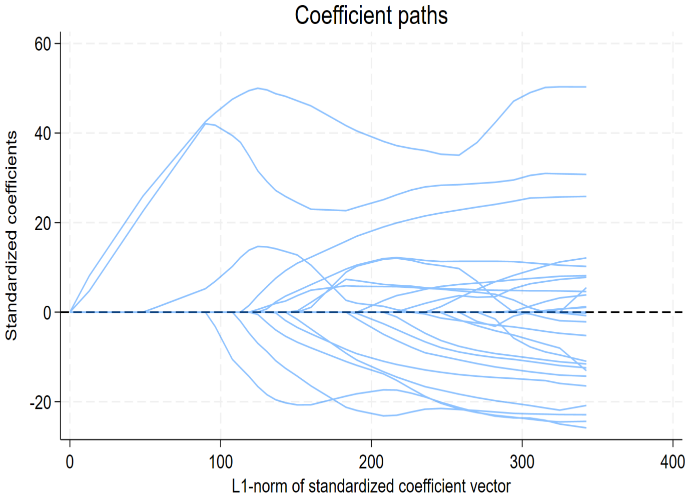
39	last lambda	3.352543	28	0.0501	314281.9

```
* lambda selected by cross-validation.
```

- Notice that the number of nonzero coefficients increases as λ decreases

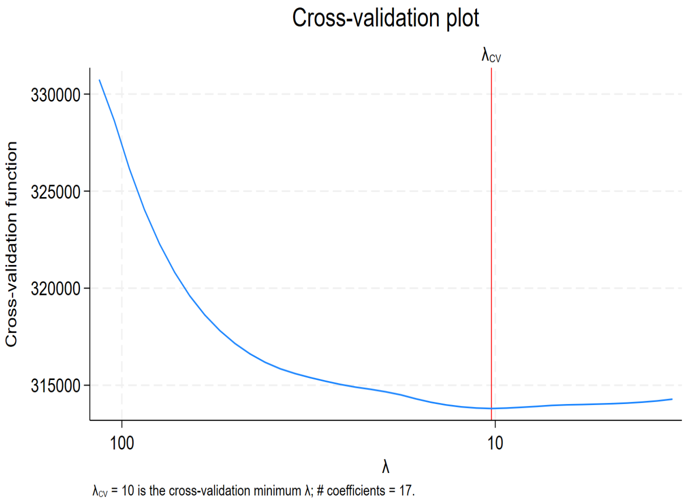
Plot path of coefficients after lasso

```
. coefpath
```



Plot cross-validation function after lasso

```
. cvplot
```



Display knot table (**lassoknots**)

```
. lassoknots

-------------------------------------------------------------------------------
       |                No. of   CV mean |
       |               nonzero     pred. |          Variables (A)dded, (R)emoved,
    ID |     lambda      coef.     error |               or left (U)nchanged
-------+---------------------------------+-------------------------------------
     2 |    104.791          2  328633.1 | A 0.msmoke#c.mage
       |                                 |   1.mmarried#c.fedu
     6 |   72.22835          3  320818.5 | A 0.msmoke#c.fedu
    11 |   45.36151          4  316613.1 | A 0.mmarried
(output omitted)
  * 27 |   10.23818         17  313799.9 | U
    28 |    9.32865         19  313823.9 | A 1.mhisp#c.medu
       |                                 |   2.msmoke#c.fage
    29 |   8.499919         18  313863.1 | R 0.msmoke#c.fedu
(output omitted)
    39 |   3.352543         28  314281.9 | A c.mage#c.monthslb
       |                                 |   0.prenatal1#c.mage
-------------------------------------------------------------------------------
* lambda selected by cross-validation.
```

Display knot table (`lassoknots`)

```
. lassoknots

-------------------------------------------------------------------------------------------
     |                  No. of   CV mean |
     |                 nonzero     pred. |       Variables (A)dded, (R)emoved,
  ID |     lambda        coef.     error |            or left (U)nchanged
-------------------------------------------------------------------------------------------
   2 |    104.791            2  328633.1 | A 0.msmoke#c.mage
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(output omitted)
  39 |   3.352543           28  314281.9 | A c.mage#c.monthslb
     |                                   |   0.prenatal1#c.mage
-------------------------------------------------------------------------------------------
* lambda selected by cross-validation.
```

- **`lassoselect`** can be used to pick a different λ value (sensitivity analysis)

Methods for selecting the value of λ

- Cross-validation (default) computes out-of-sample predictions MSEs using 10 folds and selects the λ with minimum MSE (**`selection(cv)`**)

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- Bayesian information criteria (BIC) finds λ that minimizes the BIC statistic (**`selection(bic)`**, Stata 17)
- Manual selection (**`lassoselect`**)

Choosing λ using the **selection()** option

```
. quietly lasso linear bweight $covs
. estimates store cv
. quietly lasso linear bweight $covs, selection(adaptive)
. estimates store adaptive
. quietly lasso linear bweight $covs, selection(plugin)
. estimates store plugin
. quietly lasso linear bweight $covs, selection(bic)
. estimates store bic
```

Display basic information about lassos (**lassoinfo**)

```
. lassoinfo cv adaptive plugin bic
    Estimate: cv
     Command: lasso
```

Dependent variable	Model	Selection method	Selection criterion	lambda	No. of selected variables
bweight	linear	cv	CV min.	9.867787	19

```
    Estimate: adaptive
     Command: lasso
```

Dependent variable	Model	Selection method	Selection criterion	lambda	No. of selected variables
bweight	linear	adaptive	CV min.	3.64e+08	13

```
    Estimate: plugin
     Command: lasso
```

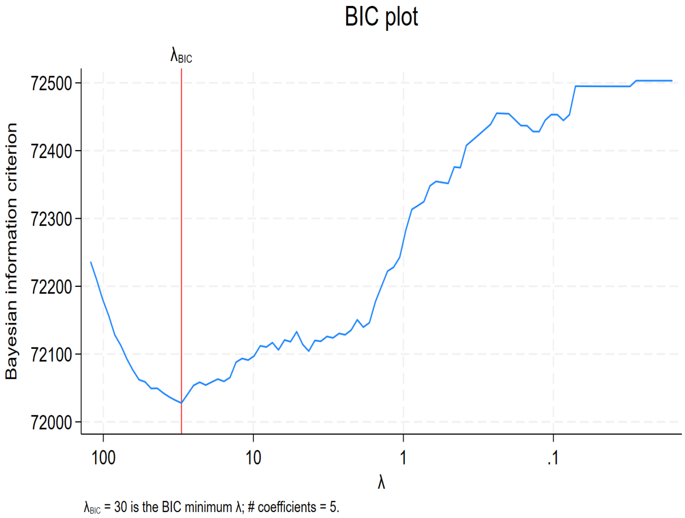
Dependent variable	Model	Selection method	lambda	No. of selected variables
bweight	linear	plugin	.0627659	6

```
    Estimate: bic
     Command: lasso
```

Dependent variable	Model	Selection method	Selection criterion	lambda	No. of selected variables
bweight	linear	bic	BIC min.	30.1348	5

Plot Bayesian information criterion function after lasso

```
. bicplot
```



Display coefficients after lasso (`lassocoef`)

```
. lassocoef cv adaptive plugin bic, display(coef, standardized)
```

	cv	adaptive	plugin	bic
mmarried				
Not married	-22.11483	-41.92165	-3.921652	-13.51986
Married	8.19e-10		3.38e-10	
msmoke				
0 daily	19.53755			
mmarried#c.fage				
Not married	-7.447833	-5.868928		
mmarried#c.medu				
Not married	-1.549706			
Married	16.17073	15.6786	21.32031	14.89484
mmarried#c.fedu				
Married	13.60921		16.50398	19.33894
foreign#c.fage				
1	-4.972952	-17.05522		
foreign#c.fedu				
0	3.90694			
alcohol#c.mage				
1	-3.167769	-6.859747		
msmoke#c.mage				
0 daily	52.73363	84.46094	57.27693	63.43016

(output omitted)

Lasso for inference

Motivation

- Ideally we would have a correct model for both data and theory. If so, we would just need to fit the model (using an appropriate estimator) and we report point estimates, standard errors, p-values, and confidence intervals

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$$\mathbf{E}[y|\mathbf{d},\mathbf{x}] = \mathbf{d}\alpha + \beta_0 + \mathbf{x}\beta'$$

    - We may fit many models with different subsets of controls

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  - But, if we do not account for the model-selection process, inference would be invalid

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  - We may fit many models with different subsets of controls
  - And, we would choose a model that we believe is the "best" to represent our theory or proposition. We apply an estimator and perform statistical inference
  - But, if we do not account for the model-selection process, inference would be invalid
- Suppose there are many potential controls. Which controls should we include in the model? How to perform valid inference on the variables of interest?

Invalid approach

1. Apply lasso for y on the variables of interest (**d** vector) and the controls (**x** vector) forcing the variables of interest to be in the model. This selects a subset of controls (**x**$*$ vector)

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- This approach would produce invalid statistical inference. Why?
    - Model-selection techniques inevitably make mistakes selecting controls
    - The actual sampling distribution of α is not concentrated (multiple modes). (Leeb and Pötscher, 2005)

Solutions

- Double selection: Belloni et al. (2014), Belloni et al. (2016) (**`dsregress`**, **`dslogit`**, and **`dspoisson`**)

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- "These solutions all use multiple lassos and moment conditions that are robust to the model-selection mistakes that lasso makes"

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- "These solutions all use multiple lassos and moment conditions that are robust to the model-selection mistakes that lasso makes"
- By default, all of the command above fit the lassos using **`selection(plugin)`**

Example on lasso for inference with a linear model

$$\mathbf{E}[y|\mathbf{d},\mathbf{x}] = \mathbf{d}\boldsymbol{\alpha} + \beta_0 + \mathbf{x}\boldsymbol{\beta}'$$

- y = wage (monthly wages)

Example on lasso for inference with a linear model

$$\mathbf{E}[y|\mathbf{d},\mathbf{x}] = \mathbf{d}\boldsymbol{\alpha} + \beta_0 + \mathbf{x}\boldsymbol{\beta}'$$

- y = wage (monthly wages)
- $\mathbf{d}$ = (educ, tenure)
  - educ: Years of education
  - tenure: Years with current employer

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$$\mathbf{E}[y|\mathbf{d},\mathbf{x}] = \mathbf{d}\boldsymbol{\alpha} + \beta_0 + \mathbf{x}\boldsymbol{\beta}'$$

- y = wage (monthly wages)
- $\mathbf{d}$ = (educ, tenure)
  - educ: Years of education
  - tenure: Years with current employer
- $\mathbf{x}$: vector of potential control variables
  - 6 continuous variables, 1 categorical variable, 5 binary variables
  - All main effects and all possible interactions generate 230 controls

Example on lasso for inference with a linear model

$$\mathbf{E}[y|\mathbf{d},\mathbf{x}] = \mathbf{d}\boldsymbol{\alpha} + \beta_0 + \mathbf{x}\boldsymbol{\beta}'$$

- y = wage (monthly wages)
- **d** = (educ, tenure)
  - educ: Years of education
  - tenure: Years with current employer
- **x**: vector of potential control variables
  - 6 continuous variables, 1 categorical variable, 5 binary variables
  - All main effects and all possible interactions generate 230 controls
- Number of observations: 722

Example on lasso for inference with a linear model

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- **d** = (educ, tenure)
  - educ: Years of education
  - tenure: Years with current employer
- **x**: vector of potential control variables
  - 6 continuous variables, 1 categorical variable, 5 binary variables
  - All main effects and all possible interactions generate 230 controls
- Number of observations: 722
- Which controls should we include in the model to perform valid inference on α?

dsregress – Double-selection lasso linear regression

```
. use nlsy80

. global controls c.(meduc feduc sibs age iq kww)##(exper ///
>         pcollege married black south urban)

. dsregress wage educ tenure, controls($controls)

Estimating lasso for wage using plugin
Estimating lasso for educ using plugin
Estimating lasso for tenure using plugin

Double-selection linear model          Number of obs               =        722
                                       Number of controls          =        230
                                       Number of selected controls =         12
                                       Wald chi2(2)                =      17.03
                                       Prob > chi2                 =     0.0002

------------------------------------------------------------------------------
             |               Robust
        wage | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        educ |   29.29732    7.58747     3.86   0.000     14.42615    44.16849
      tenure |   5.105178   2.950394     1.73   0.084     -.677488    10.88784
------------------------------------------------------------------------------
Note: Chi-squared test is a Wald test of the coefficients of the variables
      of interest jointly equal to zero. Lassos select controls for model
      estimation. Type lassoinfo to see number of selected variables in each
      lasso.

. estimates store ds_plugin
```

dsregress – Double-selection lasso linear regression

```
. use nlsy80
. global controls c.(meduc feduc sibs age iq kww)##(exper ///
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Estimating lasso for wage using plugin
Estimating lasso for educ using plugin
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------------------------------------------------------------------------------
Note: Chi-squared test is a Wald test of the coefficients of the variables
      of interest jointly equal to zero. Lassos select controls for model
      estimation. Type lassoinfo to see number of selected variables in each
      lasso.
. estimates store ds_plugin
```

- Inference on controls would not be valid; and so, they are not reported

poregress – Partialing-out lasso linear regression

```
. poregress wage educ tenure, controls($controls)
Estimating lasso for wage using plugin
Estimating lasso for educ using plugin
Estimating lasso for tenure using plugin
Partialing-out linear model           Number of obs                =        722
                                      Number of controls           =        230
                                      Number of selected controls  =         12
                                      Wald chi2(2)                 =      17.77
                                      Prob > chi2                  =     0.0001

------------------------------------------------------------------------------
             |               Robust
        wage | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        educ |   29.61345   7.455942     3.97   0.000     15.00007    44.22683
      tenure |   4.995759   2.874894     1.74   0.082     -.63893     10.63045
------------------------------------------------------------------------------
Note: Chi-squared test is a Wald test of the coefficients of the variables
      of interest jointly equal to zero. Lassos select controls for model
      estimation. Type lassoinfo to see number of selected variables in each
      lasso.
```

xporegress – Cross-fit partialing-out lasso linear regression

```
. xporegress wage educ tenure, controls($controls)

(output omitted)

Cross-fit partialing-out               Number of obs                  =        722
linear model                           Number of controls             =        230
                                       Number of selected controls    =         25
                                       Number of folds in cross-fit   =         10
                                       Number of resamples            =          1
                                       Wald chi2(2)                   =      18.00
                                       Prob > chi2                    =     0.0001

------------------------------------------------------------------------------
             |               Robust
        wage | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        educ |   29.62034   7.430891     3.99   0.000     15.05606    44.18462
      tenure |   5.082955   2.808093     1.81   0.070    -.420805    10.58672
------------------------------------------------------------------------------
Note: Chi-squared test is a Wald test of the coefficients of the variables
      of interest jointly equal to zero. Lassos select controls for model
      estimation. Type lassoinfo to see number of selected variables in each
      lasso.
```

lassoinfo after **xporegress**

```
. lassoinfo

    Estimate: active
     Command: xporegress
```

Variable	Model	Selection method	No. of selected variables: min	median	max
educ	linear	plugin	5	7	9
tenure	linear	plugin	1	2	3
wage	linear	plugin	4	6	8

lassoinfo after xporegress

```
. lassoinfo

    Estimate: active
     Command: xporegress

            |                        No. of selected variables
            |            Selection
   Variable |      Model     method      min    median      max
------------+---------------------------------------------------
       educ |     linear     plugin        5         7        9
     tenure |     linear     plugin        1         2        3
       wage |     linear     plugin        4         6        8
```

- By default, **lassoinfo** displays summary of lassos by variable

`lassoinfo` after `xporegress`

```
. lassoinfo

    Estimate: active
     Command: xporegress
```

Variable	Model	Selection method	No. of selected variables: min	median	max
educ	linear	plugin	5	7	9
tenure	linear	plugin	1	2	3
wage	linear	plugin	4	6	8

- By default, **`lassoinfo`** displays summary of lassos by variable
- The option **`each`** would display information of each lasso

General advice

- The cross-fit partialing-out estimators are the best ones (**`xporegress`**, **`xpologit`**, **`xpopoisson`**, **`xpoivregress`**). But, computations may take extremely long time

General advice

- The cross-fit partialing-out estimators are the best ones (**`xporegress`**, **`xpologit`**, **`xpopoisson`**, **`xpoivregress`**). But, computations may take extremely long time
- If you do not have the time, use either the partialing-out estimator (**`poregress`**, **`pologit`**, **`popoisson`**, **`poivregress`**) or the double-selection estimator (**`dsregress`**, **`dslogit`**, **`dspoisson`**)

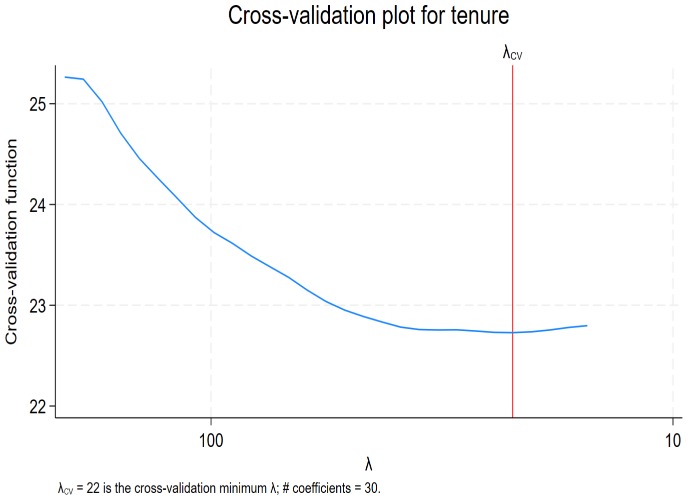
Customize individual lassos

```
. dsregress wage educ tenure,controls($controls) ///
>   lasso(wage,selection(adaptive)) ///
>   lasso(educ,selection(bic)) ///
>   sqrtlasso(tenure,selection(cv))
Estimating lasso for wage using adaptive
Estimating lasso for educ using BIC
Estimating square-root lasso for tenure using cv
Double-selection linear model          Number of obs               =        722
                                       Number of controls          =        230
                                       Number of selected controls =         54
                                       Wald chi2(2)                =      18.28
                                       Prob > chi2                 =     0.0001

------------------------------------------------------------------------------
             |               Robust
        wage | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        educ |   34.66224   8.708087     3.98   0.000      17.5947    51.72978
      tenure |   4.881471   3.095039     1.58   0.115    -1.184694    10.94764
------------------------------------------------------------------------------
Note: Chi-squared test is a Wald test of the coefficients of the variables
      of interest jointly equal to zero. Lassos select controls for model
      estimation. Type lassoinfo to see number of selected variables in each
      lasso.
```

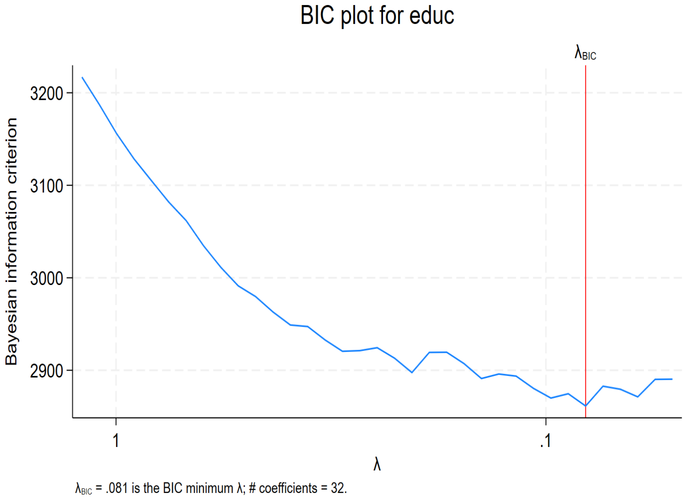
`cvplot` for a particular lasso

```
. cvplot, for(tenure)
```



`bicplot` for a particular lasso

```
.  bicplot, for(educ)
```



Other options for selecting controls

```
. quietly dsregress wage educ tenure, controls($controls) selection(cv)
. estimates store ds_cv
. quietly dsregress wage educ tenure, controls($controls) selection(adaptive)
. estimates store ds_adapt
. quietly dsregress wage educ tenure, controls($controls) selection(bic)
. estimates store ds_bic
. estimates table ds_plugin ds_cv ds_adapt ds_bic, b(%9.4f) se(%9.4f) p(%9.4f)
```

Variable	ds_plugin	ds_cv	ds_adapt	ds_bic
educ	29.2973	32.8323	34.1067	33.3164
	7.5875	8.8374	8.6690	8.6672
	0.0001	0.0002	0.0001	0.0001
tenure	5.1052	5.1631	4.8216	4.6522
	2.9504	3.0597	3.0784	3.0064
	0.0836	0.0915	0.1173	0.1218

Legend: b/se/p

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  - Using lasso for prediction and listing the selected variables in estimation commands will generally lead to invalid statistical inference. Instead, use lasso inferential commands
  - Use cross-fit partialing-out estimators if you have the time; otherwise, use either the partialing-out estimator or the double-selection estimator

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