Title

lassoinfo — Display information about lasso estimation results

Description	Quick start	Menu	Syntax
Option	Remarks and examples	Stored results	Also see

Description

`lassoinfo` displays basic information about the lasso or lassos fit by all commands that fit lassos.

Quick start

After any command that fits lassos

```
lassoinfo
```

`dsregress` was run and the results stored under the name `mygreatmodel` using `estimates store`; show information about all the lassos in `mygreatmodel`

```
lassoinfo mygreatmodel
```

As above, but three models were stored

```
lassoinfo mygreatmodel mygoodmodel myfairmodel
```

After an `xpo` command, show information about every single lasso fit

```
lassoinfo, each
```

Menu

Statistics > Postestimation

Syntax

For all lasso estimation results

`lassoinfo` [*namelist*]

For `xpo` *estimation results*

`lassoinfo` [*namelist*] [, `each`]

namelist is a name of a stored estimation result, a list of names, `_all`, or `*`. `_all` and `*` mean the same thing. See [R] **estimates store**.

`collect` is allowed; see [U] **11.1.10 Prefix commands**.

Option

each applies to xpo models only. It specifies that information be shown for each lasso for each cross-fit fold to be displayed. If resample was specified, then information is shown for each lasso for each cross-fit fold in each resample. By default, summary statistics are shown for the lassos.

Remarks and examples

stata.com

lassoinfo is intended for use after ds, po, xpo commands and after telasso to see basic information about the lassos they fit. It is a good idea to *always* run lassoinfo after these commands to see how many variables were selected in each lasso.

Running lassoinfo is a first step toward doing a sensitivity analysis. The lassos listed by lassoinfo can be examined using coefpath, cvplot, lassocoef, lassoknots, and lassoselect.

▷ Example 1: lasso

lassoinfo works after lasso, sqrtlasso, and elasticnet, but it does not display much useful information for these commands.

Here is an example using lasso from [LASSO] **lasso examples**. We load the data and make the vl variable lists active.

```
. use https://www.stata-press.com/data/r17/fakesurvey_vl
(Fictitious survey data with vl)
. vl rebuild
Rebuilding vl macros ...
  (output omitted )
```

We fit the lasso.

```
. lasso linear q104 $idemographics $ifactors $vlcontinuous, rseed(1234)
10-fold cross-validation with 100 lambdas ...
Grid value 1:     lambda = .9090511   no. of nonzero coef. =       0
Folds: 1...5....10   CVF = 18.33331
  (output omitted )
Grid value 28:    lambda = .0737359   no. of nonzero coef. =      80
Folds: 1...5....10   CVF = 11.92887
... cross-validation complete ... minimum found
Lasso linear model                          No. of obs        =        914
                                            No. of covariates =        277
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	.9090511	0	-0.0010	18.33331
23	lambda before	.1174085	58	0.3543	11.82553
* 24	selected lambda	.1069782	64	0.3547	11.81814
25	lambda after	.0974746	66	0.3545	11.8222
28	last lambda	.0737359	80	0.3487	11.92887

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

`lassoinfo` tells us nothing new.

```
. lassoinfo
    Estimate: active
     Command: lasso
```

Dependent variable	Model	Selection method	Selection criterion	lambda	No. of selected variables
q104	linear	cv	CV min.	.1069782	64

Replaying the command gives more information.

```
. lasso
Lasso linear model                          No. of obs        =        914
                                            No. of covariates =        277
Selection: Cross-validation                 No. of CV folds   =         10
```

ID	Description	lambda	No. of nonzero coef.	Out-of-sample R-squared	CV mean prediction error
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* lambda selected by cross-validation.

◁

▷ Example 2: dsregress

`lassoinfo` gives important information after the `ds`, `po`, and `xpo` commands.

We load the data used in [LASSO] **lasso examples**. See that entry for details about the data.

```
. use https://www.stata-press.com/data/r17/fakesurvey_vl, clear
(Fictitious survey data with vl)
. vl rebuild
Rebuilding vl macros ...
  (output omitted)
```

We are going to fit a `dsregress` model with `q104` as our dependent variable and variables of interest `q41` and `q22`. These variables of interest are currently in the variable lists `factors` and `vlcontinuous`, which we will use to specify the control variables. So we need to move them out of these variable lists.

```
. vl modify factors = factors - (q41)
note: 1 variable removed from $factors.
. vl move (q22) vlother
note: 1 variable specified and 1 variable moved.
  (output omitted)
. vl rebuild
Rebuilding vl macros ...
  (output omitted)
```

After we moved the variables out of the variable lists, we typed `vl rebuild` to update the variable list `ifactors` created from `factors`. See [D] **vl** for details.

We fit our `dsregress` model using cross-validation to select λ^*'s in the lassos.

```
. dsregress q104 i.q41 q22,
> controls(($idemographics) $ifactors $vlcontinuous)
> selection(cv) rseed(1234)
Estimating lasso for q104 using cv
Estimating lasso for 1bn.q41 using cv
Estimating lasso for q22 using cv
Double-selection linear model         Number of obs               =        914
                                      Number of controls          =        274
                                      Number of selected controls =        119
                                      Wald chi2(2)                =      10.96
                                      Prob > chi2                 =     0.0042
```

q104	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
q41						
Yes	.6003918	.2848483	2.11	0.035	.0420994	1.158684
q22	-.0681067	.0306219	-2.22	0.026	-.1281246	-.0080888

```
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` shows us how many variables were selected in each lasso.

```
. lassoinfo
    Estimate: active
     Command: dsregress
```

Variable	Model	Selection method	Selection criterion	lambda	No. of selected variables
q104	linear	cv	CV min.	.1132914	59
1bn.q41	linear	cv	CV min.	.0137972	64
q22	linear	cv	CV min.	.1648102	45

`lassoinfo` also gives useful information after fitting the model using the default `selection(plugin)`.

```
. dsregress q104 i.q41 q22, controls(($idemographics) $ifactors $vlcontinuous)
Estimating lasso for q104 using plugin
Estimating lasso for 1bn.q41 using plugin
Estimating lasso for q22 using plugin
Double-selection linear model         Number of obs               =        914
                                      Number of controls          =        274
                                      Number of selected controls =         29
                                      Wald chi2(2)                =      18.72
                                      Prob > chi2                 =     0.0001
```

q104	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
q41						
Yes	.8410538	.2691082	3.13	0.002	.3136114	1.368496
q22	-.0878443	.0310435	-2.83	0.005	-.1486884	-.0270001

```
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
    Estimate: active
     Command: dsregress
```

Variable	Model	Selection method	lambda	No. of selected variables
q104	linear	plugin	.1467287	14
1bn.q41	linear	plugin	.1467287	12
q22	linear	plugin	.1467287	11

See [LASSO] **lassoselect**, where we continue this example and do a sensitivity analysis to examine the differences between the lassos fit using cross-validation and the lassos fit using the plugin estimator.

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▷ Example 3: poivregress

We want to show you some differences that arise when you fit models containing endogenous variables using `poivregress` and `xpoivregress`.

We will not describe the data or the model here. See [LASSO] **Inference examples**.

We load the data,

```
. use https://www.stata-press.com/data/r17/mroz2, clear
```

set `vl` variable lists,

```
. vl create vars       = (kidslt6 kidsge6 age husage city exper)
note: $vars initialized with 6 variables.
. vl substitute vars2 = c.vars c.vars#c.vars
. vl create iv         = (huseduc motheduc fatheduc)
note: $iv initialized with 3 variables.
. vl substitute iv2    = c.iv c.iv#c.iv
```

and fit our model using `poivregress`.

```
. poivregress lwage (educ = $iv2), controls($vars2) selection(cv) rseed(12345)
Estimating lasso for lwage using cv
Estimating lasso for educ using cv
Estimating lasso for pred(educ) using cv
Partialing-out IV linear model      Number of obs                =        428
                                    Number of controls           =         27
                                    Number of instruments        =          9
                                    Number of selected controls  =         16
                                    Number of selected instruments =        4
                                    Wald chi2(1)                 =      11.10
                                    Prob > chi2                  =     0.0009
```

lwage	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
educ	.0765154	.0229707	3.33	0.001	.0314936	.1215371

```
Endogenous: educ
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 poivregresscv
```

We stored our estimation results using `estimates store`, and here we use `lassoinfo` with the name used to store them.

```
. lassoinfo poivregresscv

    Estimate: poivregresscv
     Command: poivregress
```

Variable	Model	Selection method	Selection criterion	lambda	No. of selected variables
lwage	linear	cv	CV min.	.0353704	3
educ	linear	cv	CV min.	.0530428	10
pred(educ)	linear	cv	CV min.	.013186	12

Note that we have two lassos for `educ` labeled by `lassoinfo` as `educ` and `pred(educ)`. `poivregress` and `xpoivregress` perform two lassos for each endogenous variable, one for the endogenous variable and one for its prediction. `lassoinfo` shows us how to refer to each of these lassos in other postestimation commands using the `for()` option. In this example, we would type `for(educ)` and `for(pred(educ))`, respectively.

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▷ Example 4: xporegress

The `xpo` commands fit many lassos. For each lasso fit by a `po` command, the corresponding `xpo` command fits `xfolds(#)` × `resample(#)` lassos. `lassoinfo` can be used to get information about these lassos.

We will not describe the data or the model here. See [LASSO] **Inference examples**.

We load the data,

```
. use https://www.stata-press.com/data/r17/breathe, clear
(Nitrogen dioxide and attention)
```

set `vl` variable lists,

```
. vl set
  (output omitted )
. vl move (siblings_old siblings_young) vlcontinuous
note: 2 variables specified and 2 variables moved.
  (output omitted )
. vl create mycontinuous   = vlcontinuous - (react no2_class)
note: $mycontinuous initialized with 10 variables.
. vl substitute mycontrols = i.vlcategorical mycontinuous
```

and fit our model using xporegress with the options xfolds(3) and resample(2).

```
. xporegress react no2_class, controls($mycontrols) xfolds(3) resample(2)
> selection(cv) rseed(12345)
Resample 1 of 2 ...
Cross-fit fold 1 of 3 ...
Estimating lassos: 1.
Resample 1 of 2 ...
Cross-fit fold 2 of 3 ...
Estimating lassos: 1.
Resample 1 of 2 ...
Cross-fit fold 3 of 3 ...
Estimating lassos: 1.
Resample 2 of 2 ...
Cross-fit fold 1 of 3 ...
Estimating lassos: 1.
Resample 2 of 2 ...
Cross-fit fold 2 of 3 ...
Estimating lassos: 1.
Resample 2 of 2 ...
Cross-fit fold 3 of 3 ...
Estimating lassos: 1.
Cross-fit partialing-out            Number of obs               =      1,036
linear model                        Number of controls          =         32
                                    Number of selected controls =         27
                                    Number of folds in cross-fit =         3
                                    Number of resamples         =          2
                                    Wald chi2(1)                =      20.99
                                    Prob > chi2                 =     0.0000
```

react	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
no2_class	2.332193	.5090902	4.58	0.000	1.334394	3.329991

```
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.
```

For each cross-fit fold and each resample, xporegress fits lassos. So it fit six lassos for the dependent variable, react, and six for the variable of interest, no2_class. lassoinfo summarizes the numbers of variables selected across these six lassos for react and no2_class.

```
. lassoinfo
    Estimate: active
     Command: xporegress
```

Variable	Model	Selection method	No. of selected variables min	median	max
no2_class	linear	cv	11	15	15
react	linear	cv	9	15	19

Specifying the option each gives us information on each lasso.

```
. lassoinfo, each

    Estimate: active
     Command: xporegress
```

Dependent variable	Model	Selection method	Resample number	xfold no.	Selection criterion	lambda	No. of sel. var.
no2_class	linear	cv	1	1	CV min.	.2663004	11
no2_class	linear	cv	1	2	CV min.	.2860957	15
no2_class	linear	cv	1	3	CV min.	.2887414	14
no2_class	linear	cv	2	1	CV min.	.2337636	15
no2_class	linear	cv	2	2	CV min.	.2824076	15
no2_class	linear	cv	2	3	CV min.	.2515777	15
react	linear	cv	1	1	CV min.	6.07542	9
react	linear	cv	1	2	CV min.	1.704323	19
react	linear	cv	1	3	CV min.	3.449884	15
react	linear	cv	2	1	CV min.	6.034922	9
react	linear	cv	2	2	CV min.	4.31785	16
react	linear	cv	2	3	CV min.	4.096779	15

See [LASSO] **lassocoef** for an example where we list the variables selected by each lasso.

◁

Stored results

lassoinfo stores the following in r():

Macros
- r(names) names of estimation results displayed

Matrices
- r(table) matrix containing the numerical values displayed

Also see

[LASSO] **lassoselect** — Select lambda after lasso

[LASSO] **lasso postestimation** — Postestimation tools for lasso for prediction

[LASSO] **lasso inference postestimation** — Postestimation tools for lasso inferential models