dstat: A unified framework for estimation of summary statistics and distribution functions

Ben Jann

University of Bern

German Stata Conference
Online, June 25, 2021

Outline

Why this command?

- Stata provides great functionality for advanced statistics and econometric analyses.
- However, Stata sometimes appears a bit weak in terms of descriptive statistics.
- What do I mean by descriptive statistics?
  - Statistics describing points in a distribution; series of such statistics illustrate the shape of a distribution.
    - Densities, cumulative distributions, histograms, probabilities, quantiles, lorenz ordinates, etc.
  - Summary statistics describing particular features of a distribution.
    - Various types of location, dispersion, skewness, or kurtosis measures.
    - Inequality, concentration, and poverty measures.
    - ...?
  - I primarily mean univariate statistics (although some of the measures covered by `dstat` are bivariate and `dstat` has some other features to support "multivariate" analyses).

What do I mean by "weak"?

- With "weak" I do not mean that descriptive statistics cannot be computed in Stata. I just mean that things could be a bit improved in terms of functionality and convenience.
  - Different types of statistics are scattered across various commands.
  - Each command has its own logic (idiosyncratic syntax, idiosyncratic output, idiosyncratic returns).
  - Support for statistical inference greatly varies (some commands do not even allow weights, others fully support complex survey estimation).
  - Often difficult to create tables and graphs without too much effort (particularly if interested in confidence intervals).
  - Some topics such as, e.g., inequality measures are not covered at all in official Stata. In general, there is a large number of user add-ons for descriptive statistics which, again, all have their own idiosyncrasies, and also greatly vary in terms of functionality and quality.

Guiding principles for the new command

- Descriptive statistics are estimates and should be treated as such.
  - Provide standard errors/confidence intervals for everything.
  - Standardized output like any other estimation command.
  - Return results in `e()` like any other estimation command.
- Highly standardized and consistent, but as flexible as possible.
- Graphs are important in descriptive analysis; provide convenient graphing functionality.
- Framework should be easy to extend (integrate further statistics without too much effort).
- Personal interest: Provide support for covariate balancing a.k.a. compositional standardization ($\rightarrow$ treatment effect estimation, counterfactual decompositions).

Moment conditions and influence functions

- Think of statistic θ as a functional of a distribution F, that is $\theta = T(F)$.
- The influence function of θ is defined as the limit of the change in θ if a small amount of data mass is added at a specific point in the distribution:

$$\text{IF}(x, \theta, F) = \lim_{\epsilon \to 0} \frac{T((1-\epsilon)F + \epsilon\delta_x) - T(F)}{\epsilon}$$

  where δ_x is a distribution with all its mass at point x.
- Influence functions have been developed in robust statistics (e.g. Hampel 1974) to study the robustness properties of estimators.
- However, influence functions are super useful because the sampling variance of an estimator is equal to the sampling variance of the expected value of its influence function (e.g. Deville 1999)
- This means that the standard error of a mean estimate of the "empirical" influence function provides a consistent estimate of the standard error of $\hat{\theta}$.

Moment conditions and influence functions

- But how to compute influence functions in practice?
- Let h_i^θ be the moment condition of θ such that

$$\frac{1}{W}\sum_{i=1}^{n} w_i h_i^{\hat\theta} = 0$$

  where w_i are sampling weights and W is the sum of weights.
- For example, for the mean $\bar y$ of Y the moment condition is

$$h_i^{\bar y} = Y_i - \bar y$$

- The "empirical" influence function can then be obtained as

$$\mathrm{IF}_i(\hat\theta) = \frac{1}{G} h_i^{\hat\theta} \qquad \text{with} \quad G = -\frac{1}{W}\sum_{i=1}^{n} w_i \frac{\partial h_i^{\hat\theta}}{\partial \hat\theta}$$

- In case of the mean, G boils down to 1, such that the influence function simply is $\mathrm{IF}_i(\bar y) = Y_i - \bar y$.

Moment conditions and influence functions

- Many statistics are constructed in a way such that they depend on a number of auxiliary estimates. For example, the trimmed mean depends on the quantiles at which the data is trimmed.
- Influence functions for such statistics can be derived using the chain rule.
- Let θ depend on additional parameters $\gamma_1, \ldots, \gamma_k$. The influence function of θ can then be obtained as

$$\mathrm{IF}_i(\hat{\theta}) = \frac{1}{G}\left(h_i^{\hat{\theta}} - \sum_{j=1}^{k} G_j \mathrm{IF}_i(\hat{\gamma}_j)\right) \quad \text{with} \quad G_j = -\frac{1}{W}\sum_{i=1}^{n} w_i \frac{\partial h_i^{\hat{\theta}}}{\partial \hat{\gamma}_j}$$

- If γ_j itself depends on further parameters, its influence function will have a similar form. In this way we can easily piece together influence functions also for very complex statistics.

Moment conditions and influence functions

- More generally (see Jann 2020), if θ is a vector of estimates $\theta_1, \ldots, \theta_k$ that may or may not depend on each other, the (k dimensional) influence function of θ can be obtained as

$$\mathrm{IF}_i(\hat{\theta}) = \mathbf{G}^{-1}\mathbf{h}_i$$

where

$$\mathbf{h}_i = \begin{bmatrix} h_i^{\hat{\theta}_1} \\ \vdots \\ h_i^{\hat{\theta}_k} \end{bmatrix} \quad \text{and} \quad \mathbf{G} = -\frac{1}{W}\sum_{i=1}^{n} w_i \frac{\partial \mathbf{h}_i}{\partial \hat{\theta}'}$$

- As David Drukker would say:

"Stack the moment equations!"

Moment conditions and influence functions

- Although things might look complicated at first sight, obtaining influence functions is actually quite easy in most cases. Also subpopulation estimation can be integrated without much trouble and there is a very simple solution to take account of covariate balancing based on reweighting.
- Hence, influence functions are the method of choice for the new command.
- One great thing about influence functions is that support for complex survey estimation (`svy`) comes for free.
- Another great thing is that the influence function of a linear or nonlinear combination of several statistics can be obtained by linear combination of the individual influence functions (as implied by the chain rule).
- Furthermore, the RIFs (recentered influence functions) can be used in regression models to study approximate effects of covariates on a statistic (Firpo et al. 2009).

Estimation

- Distribution functions:

  `dstat` *subcmd varlist* [*if*] [*in*] [*weight*] [, *options*]

  where *subcmd* is one of `density`, `histogram`, `proportion`, `cdf`, `ccdf`, `quantile`, `lorenz`, `share`.

- Summary statistics:

  `dstat` [(*stats*)] *varlist* [(*stats*) *varlist* ...] [*if*] [*in*] [*weight*] [, *options*]

  where *stats* is a space-separated list of statistics. A large collection of statistics is available.

Available summary statistics

Points in the distribution

quantile(*p*)	*p*/100 quantile; *p* in [0,100]
p(*p*)	alias for **quantile()**
density(*x*)	kernel density at value *x*
hist(*x1*,*x2*)	histogram density of data within (*x1*,*x2*]
cdf*(*x*)	cumulative distribution (CDF) at value *x*; suffix * is empty for default, **m** for mid-adjusted CDF, **f** for floor CDF
ccdf*(*x*)	complementary CDF at value *x*; suffix * is empty for default, **m** for mid-adjusted CCDF, **f** for floor CCDF
prop(*x1*[,*x2*])	proportion of data equal to *x1* or within [*x1*,*x2*]
pct(*x1*[,*x2*])	percent of data equal to *x1* or within [*x1*,*x2*]
freq(*x1*[,*x2*])	frequency of data equal to *x1* or within [*x1*,*x2*]
total[(*x1*[,*x2*])]	overall total, or total of data equal to *x1* or within [*x1*,*x2*]
min	observed minimum (standard error set to zero)
max	observed maximum (standard error set to zero)
range	**max-min** (standard error set to zero)
midrange	(**min+max**)/2 (standard error set to zero)

Location measures

mean	arithmetic mean
gmean	geometric mean (data must be positive)
hmean	harmonic mean (data must be positive)
trim[(*p*)]	*p*/100 trimmed mean; *p* in [0,50]; default is *p*=25
trim(*p1*,*p2*)	trimmed mean with *p1*/100 lower trimming and *p2*/100 upper trimming
winsor[(*p*)]	*p*/100 winsorized mean; *p* in [0,50]; default is *p*=25
winsor(*p1*,*p2*)	winsorized mean with *p1*/100 lower winsorizing and *p2*/100 upper winsorizing
median	median; equal to **q50**
huber[(*p*)]	Huber M estimate with gaussian efficiency *p* in [63.7,99.9]; default is *p*=95
biweight[(*p*)]	biweight M estimate with gaussian efficiency *p* in [.01,99.9]; default is *p*=95
hl	Hodges-Lehmann location measure (Hodges and Lehmann 1963)

Available summary statistics

Scale measures

sd[(*df*)]	standard deviation; *df* applies small-sample adjustment; default is *df*=1
variance[(*df*)]	variance; default is *df*=1
mse[(*x*[,*df*])]	mean squared deviation from value *x* (mean squared error); default is *x*=0 and *df*=0
smse[(*x*[,*df*])]	square-root of mean squared deviation from value *x*; default is *x*=0 and *df*=0
iqr[(*p1*,*p2*)]	interquantile range; default is **iqr(25,75)** (interquartile range)
iqrn	normalized interquartile range; equal to 1 / (invnormal(0.75) - invnormal(0.25)) * **iqr**
mad[(*l*[,*t*])]	median (or mean if *l*!=0) absolute deviation from the median (or mean if *t*!=0)
madn[(*l*[,*t*])]	normalized MAD; equal to 1/invnormal(0.75) * **mad** (or sqrt(pi/2) * **mad** if *l*!=0)
mae[(*l*[,*x*])]	median (or mean if *l*!=0) absolute deviation from value *x*; default is *x*=0
maen[(*l*[,*x*])]	normalized MAE; equal to 1/invnormal(0.75) * **mae** or (sqrt(pi/2) * **mae** if *l*!=0)
md	mean absolute pairwise difference; equal to 2 * **mean** * **gini**
mdn	normalized mean absolute pairwise difference; equal to sqrt(pi)/2 * **md**
mscale[(*bp*)]	M estimate of scale with breakdown point *bp* in [1,50]; default is *bp*=50
qn	Qn scale coefficient (Rousseeuw and Croux 1993)

Skewness measures

skewness	skewness
qskew[(*alpha*)]	quantile skewness (Hinkley 1975); *alpha* in [0,50]; default is *alpha*=25
mc	medcouple (Brys et al. 2004)

Kurtosis measures

kurtosis	kurtosis
qw[(*alpha*)]	quantile tail weight; *alpha* in [0,50]; default is *alpha*=25
lqw[(*alpha*)]	left quantile tail weight; *alpha* in [0,50]; default is *alpha*=25
rqw[(*alpha*)]	right quantile tail weight; *alpha* in [0,50]; default is *alpha*=25
lmc	left medcouple tail weight measure (Brys et al. 2006)
rmc	right medcouple tail weight measure (Brys et al. 2006)

Available summary statistics

Inequality measures

hoover	Hoover index (Robin Hood index)
gini[(*df*)]	Gini coefficient; *df* applies small-sample adjustment; default is *df*=0
agini[(*df*)]	absolute Gini coefficient
mld	mean log deviation; equal to **ge(0)**
theil	Theil index; equal to **ge(1)**
cv[(*df*)]	coefficient of variation; default is *df*=1; **cv(0)**=sqrt(2***ge(1)**)
ge[(*alpha*)]	generalized entropy (Shorrocks 1980) with parameter *alpha*
atkinson[(*epsilon*)]	Atkinson index with parameter *epsilon*>=0; default is *epsilon*=1
lvar[(*df*)]	logarithmic variance; default is *df*=1
vlog[(*df*)]	variance of logarithm; default is *df*=1
top[(*p*)]	outcome share of top *p* percent; default is *p*=10
bottom[(*p*)]	outcome share of bottom *p* percent; default is *p*=40
mid[(*p1*,*p2*)]	outcome share of mid *p1* to *p2* percent; default is *p1*=40 and *p2*=90
palma	palma ratio; equal to **top/bottom** or **sratio(40,90)**
qratio[(*p1*,*p2*)]	quantile ratio **q**(*p2*)/**q**(*p1*); default is *p1*=10 and *p2*=90
sratio[(*u1*,*l2*)]	percentile share ratio; default is *u1*=10 and *l2*=90
sratio[(*l1*,*u1*,*l2*,*u2*)]	percentile share ratio; default is *l1*=0, *u1*=10, *l2*=90, *u2*=100
***lorenz**(*p*)	Lorenz ordinate, *p* in [0,100]; prefix * is empty for default, **g** for generalized, **t** for total, **a** for absolute, **e** for equality gap
***share**(*p1*,*p2*)	percentile share, *p1* and *p2* in [0,100]; prefix * is empty for default, **d** for density, **g** for generalized, **t** for total, **a** for average

Available summary statistics

Concentration measures

gci(*zvar*[,*df*]**)**	Gini concentration index; *zvar* specifies the sort variable; *df* applies small-sample adjustment; default is *df*=0
gci[(*df*)]	**gci** using sort variable from option **zvar()**
aci(*zvar*[,*df*]**)**	absolute Gini concentration index; *zvar* and *df* are as for **gci**
aci[(*df*)]	**aci** using sort variable from option **zvar()**
*****ccurve(***p*[,*zvar*]**)**	concentration curve ordinate, *p* in [0,100]; prefix * is empty for default, **g** for generalized, **t** for total, **a** for absolute, **e** for equality gap
*****cshare(***p1*,*p2*[,*zvar*]**)**	concentration share, *p1* and *p2* in [0,100]; prefix * is empty for default, **d** for density, **g** for generalized, **t** for total, **a** for average

Poverty measures

hcr[(*pline*)]	head count ratio (i.e. proportion poor); *pline* specifies the poverty line(s) > 0; *pline* can be *varname* or #; the default is as set by option **pline()**
pgap[(*pline*)]	poverty gap (proportion by which mean outcome of poor is below poverty line)
pgi[(*pline*)]	poverty gap index; equal to **hcr*pgap**
fgt[(*a*[,*pline*])]	Foster–Greer–Thorbecke index with *a*>=0 (Foster et al. 1984, 2010); default is *a*=0 (head count ratio); *a*=1 is equivalent to **pgi**
sen[(*pline*)]	Sen poverty index (Sen 1976; using the replication invariant version of the index, also see Shorrocks 1995)
sst[(*pline*)]	Sen-Shorrocks-Thon poverty index (see, e.g., Osberg and Xu 2008)
takayama[(*pline*)]	Takayama poverty index (Takayama 1979)
watts[(*pline*)]	Watts index (see, e.g., Saisana 2014)
chu[(*a*[,*pline*])]	Clark-Hemming-Ulph poverty index with *a* in [0,100] (Clark et al. 1981); default is *a*=50; *a*=0 is equivalent to 1-exp(-**watts**); *a*=100 is equivalent to **fgt(1)**

Some main options

- over(*overvar* [, *options*]) [total]
  - compute results by subpopulations, possibly including total, possibly accumulating or taking contrasts
- balance([*method* :] *varlist* [, *options*])
  - balance covariates using IPW or entropy balancing
- nocasewise
  - exclude missing values for each variable individually (no casewise deletion of observations)
- vce(*vcetype* [, *options*])
  - note: specify `vce(svy)` for complex survey estimation instead of applying the `svy` prefix!
- There are many more options; see `help dstat` for details.

After estimation

- Draw graph:

  `dstat graph` [, *graph_options*]

  or apply option `graph()` when estimating. The graphs will be created by an internal call to `coefplot` (Jann 2014).

- Obtain (recentered) influence functions:

  `predict` { *stub** | *newvarlist* } [*if*] [*in*] [, *predict_options*]

  or apply option `generate()` when estimating.

```
. use sess16, clear
(Sample from Swiss Earnings Structure Survey 2016)

. describe

Contains data from sess16.dta
  obs:        50,000                          Sample from Swiss Earnings Structure
                                                Survey 2016
 vars:             5                          24 Jun 2021 21:38
------------------------------------------------------------------------------------------
              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------
earnings        long    %10.0g                monthly earnings in CHF (full-time
                                                equivalent)
gender          byte    %8.0g      gender     gender
educ            byte    %27.0g     educ       highest educational degree
tenure          byte    %8.0g                 tenure (in years)
wgt             double  %10.0g                sampling weight
------------------------------------------------------------------------------------------
Sorted by:

. summarize

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
    earnings |     47,600    7848.055    4189.382       2314     103998
      gender |     49,771    .5547608    .4969972          0          1
        educ |     49,503    2.797063    1.304769          1          5
      tenure |     48,525    8.599588    8.934825          0         61
         wgt |     50,000    33.19645    61.75064   8.435029   2991.433
```

- If you specify no subcommand and no statistics, `dstat` behaves like official `mean`:

```
. dstat earnings [pw=wgt], over(gender)
mean                                 Number of obs     =     47,383

--------------------------------------------------------------
    earnings |      Coef.   Std. Err.     [95% Conf. Interval]
-------------+------------------------------------------------
      gender |
     female  |   6511.388   31.48064      6449.686    6573.091
       male  |   8007.006   53.82319      7901.511      8112.5
--------------------------------------------------------------

. mean earnings [pw=wgt], over(gender)
Mean estimation                          Number of obs     =     47,383

------------------------------------------------------------------
                  |       Mean   Std. Err.     [95% Conf. Interval]
------------------+-----------------------------------------------
c.earnings@gender |
           female |   6511.388   31.48064      6449.686    6573.091
             male |   8007.006   53.82319      7901.511      8112.5
------------------------------------------------------------------
```

- Other than `mean` it allows you to include the total across subpopulations or to take contrasts:

```
. dstat earnings [pw=wgt], over(gender, contrast(1) ratio)
Ratio of mean                          Number of obs    =     47,383
                                       Contrast         =   1.gender

------------------------------------------------------------------
    earnings |      Coef.   Std. Err.      [95% Conf. Interval]
-------------+----------------------------------------------------
      gender |
      female |   .8132114   .0067335      .8000137    .8264091
------------------------------------------------------------------

. dstat earnings [pw=wgt], over(gender) total
mean                                   Number of obs    =     47,383

------------------------------------------------------------------
    earnings |      Coef.   Std. Err.      [95% Conf. Interval]
-------------+----------------------------------------------------
      gender |
      female |   6511.388   31.48064      6449.686    6573.091
        male |   8007.006   53.82319      7901.511      8112.5
             |
       total |   7366.241   34.06905      7299.465    7433.017
------------------------------------------------------------------
```

- You can also select and reorder subpopulations (total will still be across all subpopulations):

```
. dstat earnings [pw=wgt], over(educ) total
mean                                Number of obs    =     47,129
```

earnings	Coef.	Std. Err.	[95% Conf.	Interval]
educ				
Lower secondary	5093.716	38.91248	5017.447	5169.985
Upper secondary: vocational	6380.539	34.30033	6313.31	6447.768
Upper secondary: general	7438.123	141.6259	7160.534	7715.711
Tertiary: vocational	9019.856	56.53847	8909.039	9130.672
Tertiary: academic	11471.11	170.9918	11135.96	11806.25
total	7369.873	34.33644	7302.573	7437.173

```
. dstat earnings [pw=wgt], over(educ, select(5 4)) total
mean                                Number of obs    =     47,129
```

earnings	Coef.	Std. Err.	[95% Conf.	Interval]
educ				
Tertiary: academic	11471.11	170.9918	11135.96	11806.25
Tertiary: vocational	9019.856	56.53847	8909.039	9130.672
total	7369.873	34.33644	7302.573	7437.173

- Furthermore, `dstat` supports IPW covariate balancing. Here is an "ATT" of being male (earnings gap if women's sample is reweighted):

```
. dstat earnings [pw=wgt], over(gender, contrast) balance(i.educ tenure, ref(1))

Difference in mean                          Number of obs     =     45,530
                                            Contrast          =   0.gender
                                            Balancing:
                                                     method =          ipw
                                                  reference =   1.gender
                                                   controls = e(balance)

------------------------------------------------------------------------------
    earnings |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      gender |
        male |   1261.559     55.857    22.59   0.000     1152.078    1371.039
------------------------------------------------------------------------------

. teffects ipw (earnings) (gender i.educ tenure) [pw=wgt], atet nolog

Treatment-effects estimation                Number of obs     =     45,530
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
----------------------------------------------------------------------------------
                 |               Robust
        earnings |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
ATET             |
          gender |
 (male vs female)|   1261.559   55.85639    22.59   0.000     1152.082    1371.035
-----------------+----------------------------------------------------------------
POmean           |
          gender |
          female |    6755.25   34.66481   194.87   0.000     6687.308    6823.192
----------------------------------------------------------------------------------
```

- IPW does not perfectly balance the data ...

```
. dstat (pr1 pr2 pr3 pr4 pr5) educ (mean) tenure [pw=wgt] if earnings<., ///
>     over(gender, contrast) balance(i.educ tenure, ref(1))

Difference in summary statistics             Number of obs     =     45,530
                                             Contrast          =   0.gender
                                             Balancing:
                                                        method =        ipw
                                                     reference =   1.gender
                                                      controls = e(balance)

            0: gender = female
            1: gender = male

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1~educ       |
         pr1 |  -.0017249   .0005537    -3.12   0.002    -.0028101   -.0006396
         pr2 |   .0006886   .0009046     0.76   0.447    -.0010844    .0024616
         pr3 |  -.0002834   .0003077    -0.92   0.357    -.0008864    .0003197
         pr4 |   .0003433    .000665     0.52   0.606    -.0009601    .0016466
         pr5 |   .0009764   .0004809     2.03   0.042     .0000338    .0019189
-------------+----------------------------------------------------------------
1~tenure     |
        mean |   .1103688   .0254176     4.34   0.000     .0605498    .1601877
------------------------------------------------------------------------------
```

- ... so you may prefer entropy balancing:

```
. dstat earnings [pw=wgt], over(gender, contrast) balance(eb:i.educ tenure, ref(1))
Difference in mean                               Number of obs     =     45,530
                                                 Contrast          =   0.gender
                                                 Balancing:
                                                           method =         eb
                                                        reference =   1.gender
                                                         controls = e(balance)

------------------------------------------------------------------------------
    earnings |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      gender |
        male |   1247.068   55.99405    22.27   0.000     1137.318    1356.817
------------------------------------------------------------------------------

. kmatch eb gender i.educ tenure (earnings = i.educ tenure) [pw=wgt], att nomtable
(fitting balancing weights ... done)
Entropy balancing                                Number of obs     =     45,530
                                                 Balance tolerance =     .00001
Treatment   : gender = 1
Targets     : 1
Covariates  : i.educ tenure
RA equations: earnings = i.educ tenure _cons
Treatment-effects estimation
------------------------------------------------------------------------------
    earnings |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ATT |   1247.068   55.99405    22.27   0.000     1137.318    1356.817
------------------------------------------------------------------------------
```

- Perfect balance!

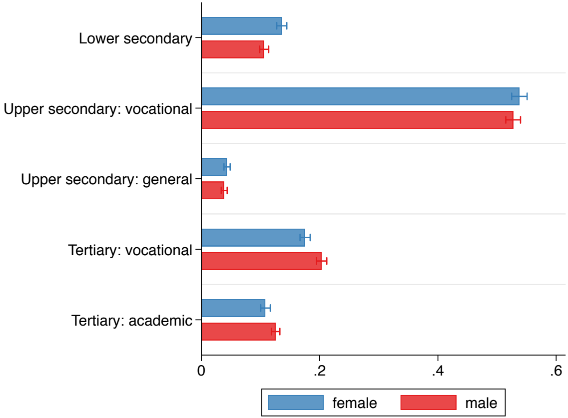
```
. dstat (pr1 pr2 pr3 pr4 pr5) educ (mean) tenure [pw=wgt] if earnings<., ///
>     over(gender, contrast) balance(eb:i.educ tenure, ref(1))

Difference in summary statistics               Number of obs     =     45,530
                                               Contrast          =   0.gender
                                               Balancing:
                                                          method =         eb
                                                       reference =   1.gender
                                                        controls = e(balance)

            0: gender = female
            1: gender = male

-----------------------------------------------------------------------------
             |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+---------------------------------------------------------------
1~educ       |
         pr1 |  -3.61e-16   2.18e-17   -16.52   0.000    -4.04e-16   -3.18e-16
         pr2 |   2.22e-16   1.52e-17    14.60   0.000     1.92e-16    2.52e-16
         pr3 |   2.08e-17   1.46e-18    14.30   0.000     1.80e-17    2.37e-17
         pr4 |   1.39e-16   6.82e-18    20.36   0.000     1.25e-16    1.52e-16
         pr5 |   6.94e-17   3.75e-18    18.52   0.000     6.20e-17    7.67e-17
-------------+---------------------------------------------------------------
1~tenure     |
        mean |  -3.55e-15   2.25e-16   -15.78   0.000    -3.99e-15   -3.11e-15
-----------------------------------------------------------------------------
```

- All of the above you can do with any other statistic, also with multiple statistics and multiple variables at the same time!

```
. generate lnearn = ln(earnings)
(2,400 missing values generated)

. dstat (mean gini mld vlog) earnings (mean var) lnearn [pw=wgt], ///
>     over(gender, contrast) balance(eb:i.educ tenure, ref(1))

Difference in summary statistics              Number of obs     =     45,530
                                              Contrast          =   0.gender
                                              Balancing:
                                                         method =         eb
                                                      reference =   1.gender
                                                       controls = e(balance)

            0: gender = female
            1: gender = male

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1~earnings   |
        mean |   1247.068   55.99405    22.27   0.000     1137.318    1356.817
        gini |   .0393687   .0038698    10.17   0.000     .0317838    .0469536
         mld |   .0298174   .0031885     9.35   0.000     .0235679     .036067
        vlog |   .0421788   .0043786     9.63   0.000     .0335967    .0507609
-------------+----------------------------------------------------------------
1~lnearn     |
        mean |   .1392601   .0056122    24.81   0.000     .1282601    .1502602
         var |   .0421788   .0043786     9.63   0.000     .0335967    .0507609
------------------------------------------------------------------------------
```

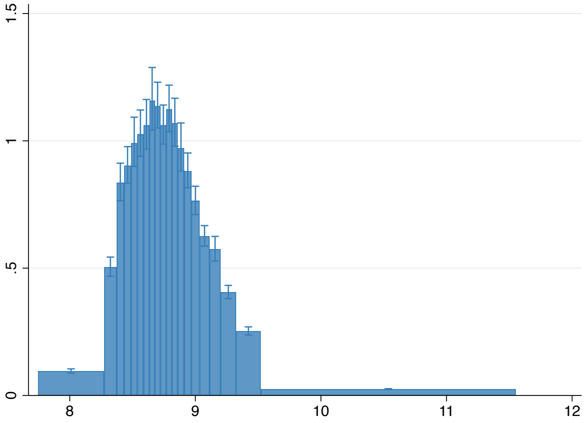
- Some other stuff. Here is the educational distribution by gender:

```
. dstat prop educ [pw=wgt], over(gender) graph(merge)
Proportion                            Number of obs     =     49,277
            0: gender = female
            1: gender = male
(coefficients table suppressed)
```



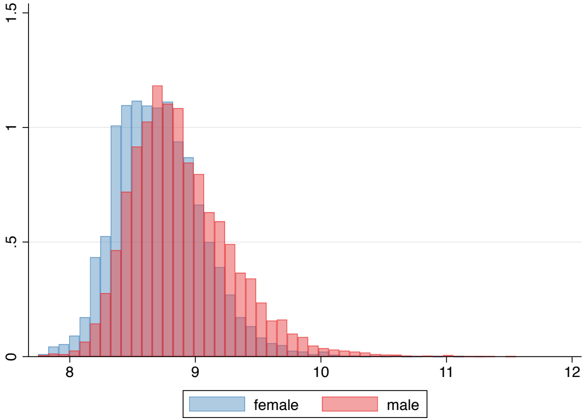
- Or an equal probability histogram of log earnings:

```
. dstat histogram lnearn [pw=wgt], ep n(20) graph
Histogram (density)                Number of obs     =      47,600
(coefficients table suppressed)
```



- Or histograms of log earnings by gender printed on top of each other using the same bin definitions:

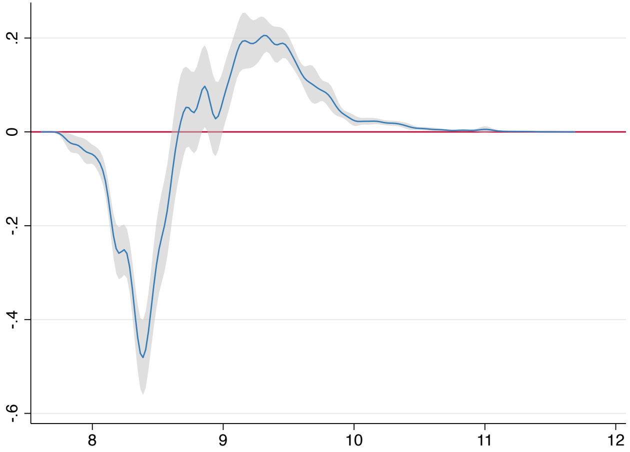
```
. dstat histogram lnearn [pw=wgt], over(gender) common nose graph(merge)
Histogram (density)                 Number of obs    =     47,383

            0: gender = female
            1: gender = male

(coefficients table suppressed)
```



- Or the difference in the density function of log earnings by gender:

```
. dstat density lnearn [pw=wgt], over(gender, contrast) n(200) ///
>     graph(yline(0))
```

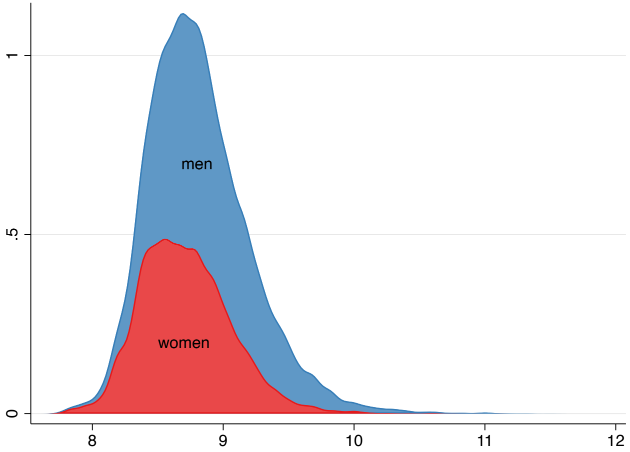
(*output omitted*)



- Or the composition of the overall density of log earnings by gender:

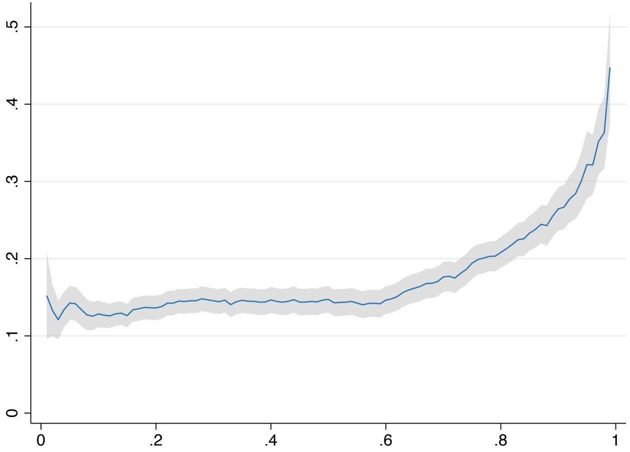
```
. dstat density lnearn [pw=wgt], over(gender) total nose n(200) unconditional ///
>     graph(recast(area) select(3 1) merge legend(off) ///
>         text(.2 8.7 "women" .7 8.8 "men"))
```

(*output omitted*)



- Or the difference in quantile functions of log earnings by gender:

```
. dstat quantile lnearn [pw=wgt], over(gender, contrast) graph(ylabel(0(.1).5))
  (output omitted)
```



- `dstat` cannot compute balanced and unbalanced results at the same time. If you want include both sets of results in the same graph, you need to store the estimates and use `coefplot` manually.
- Here is how to create a graph that shows the quantile wage gap function with and without covariate adjustment:

```
. dstat quantile lnearn [pw=wgt], over(gender, contrast) notable ///
>     balance(eb:i.educ tenure)
  (output omitted)
. estimates store balanced
. dstat quantile lnearn [pw=wgt] if e(sample), over(gender, contrast)
  (output omitted)
. estimates store raw
. coefplot raw balanced, se(se) at(at) keep(1:) ylabel(0(.1).5) ///
>     recast(line) ciopts(recast(rarea) pstyle(ci) color(%50) lcolor(%0)) ///
>     plotlabels("raw wage gap" "adjusted wage gap")
```

0
.1
.2
.3
.4
.5
0
.2
.4
.6
.8
1
raw wage gap
adjusted wage gap

Conclusions

- I could go on forever. There would be so much more to show ...
- Have fun with the command!
- Drop me a note if you want me to add a specific statistic.
- Install from SSC

  ```
  . ssc install dstat, replace
  . ssc install moremata, replace
  . ssc install coefplot, replace
  ```

  or from GitHub: http://github.com/benjann/dstat

References

- Deville, J.C. 1999. Variance estimation for complex statistics and estimators: linearization and residual techniques. Survey Methodology 25:193–203.
- Firpo, S., N.M. Fortin, T. Lemieux. 2009. Unconditional quantile regressions. Econometrica 77:953–973.
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- Jann, B. 2014. Plotting regression coefficients and other estimates. The Stata Journal 14:708-737.
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