Creating factor variables in resultssets and other datasets

Roger B. Newson
r.newson@imperial.ac.uk
http://www.imperial.ac.uk/nhli/r.newson/

National Heart and Lung Institute, Imperial College London

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The importance of string–factor (and factor–string) conversion

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- Nowadays, a commoner reason to `encode` is that string variables cannot be axis variables in graphs.
- More generally, a well–formed Stata dataset should have one observation per *thing* and data on *attributes_of_things*.
- And the *thing*s should be identified by **key variables**, by which the observations are sorted and identified uniquely.
- And, if these key variables are string, then they cannot be sorted non–alphabetically.
- *On the other hand*, numeric variables (labelled or otherwise) often need the addition of prefixes, suffixes and/or conversion of exponents before being output to TEX, HTML, RTF or SMCL.

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Some SSC programs for string–factor and factor–string conversion

Official Stata's `encode`, `decode`, `destring` and `tostring` commands seemed insufficient for what I wanted to do. So, over time, I accumulated some conversion packages of my own:

Command	*Description*
String–factor:	
`sencode`	"Super" version of `encode`
`fvregen`	Extract factors from a parameter–name string variable in a resultsset
`factext`	Extract factors from a parameter–label string variable in a resultsset
Factor–string:	
`sdecode`	"Super" version of `decode`
`msdecode`	Multi–factor version of `sdecode`
`factmerg`	Generate factor name, label and level string variables from multiple input factors
`insingap`	Insert labelled gap observations at start of by–groups
`bmjcip`	Decode estimates, confidence limits, and *P*– and *Q*–values

Resultssets may be generated by the SSC package `parmest`. The programs `msdecode`, `factmerg`, `insingap` and `bmjcip` all use `sdecode`.

The `sencode` package for string–factor conversion

- `sencode` is a "super" version of `encode`, downloadable (and frequently downloaded) from SSC.
- It has a `replace` option, so the output numeric variable can inherit the name and position of the input string variable.
- It has a `gsort()` option, specifying a list of existing variables (defaulting to `_n`), which determine the primary, non–alphabetic order in which the output numeric values will be allocated (breaking ties alphabetically).
- It has a `manyto1` option, specifying that multiple `gsort()` groups of observations with the same input string value can have different output numeric values, instead of being combined in order of first appearance of the input string value.
- `sencode` has been evolving since 2001. *However*, we will be presenting some useful tips, accumulated since then, that are not immediately obvious.

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Example: Keying and plotting the `auto` data

- The familiar `auto` dataset, loadable using `sysuse`, is not really a well–formed Stata dataset.
- The `describe` command shows that it is sorted by the binary variable `foreign`, which indicates US or non–US origin for a car model, but does not identify the car models uniquely.
- The models are in fact identified uniquely by the string variable `make`.
- We might like to encode the variable `make` to a labelled numeric variable, which we can then sort by, and plot against other variables in the dataset.
- And, to show off, we will order the new variable primarily by descending weight, breaking tied weights alphabetically.

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The `auto` data

We load the `auto` dataset, and then `describe` it:

```
. sysuse auto, clear;
(1978 Automobile Data)

. describe;

Contains data from C:\Program Files (x86)\Stata12\ado\base/a/auto.dta
  obs:            74                          1978 Automobile Data
 vars:            12                          13 Apr 2011 17:45
 size:         3,182                          (_dta has notes)
--------------------------------------------------------------------------------
              storage  display     value
variable name   type   format      label      variable label
--------------------------------------------------------------------------------
make            str18  %-18s                  Make and Model
price           int    %8.0gc                 Price
mpg             int    %8.0g                  Mileage (mpg)
rep78           int    %8.0g                  Repair Record 1978
headroom        float  %6.1f                  Headroom (in.)
trunk           int    %8.0g                  Trunk space (cu. ft.)
weight          int    %8.0gc                 Weight (lbs.)
length          int    %8.0g                  Length (in.)
turn            int    %8.0g                  Turn Circle (ft.)
displacement    int    %8.0g                  Displacement (cu. in.)
gear_ratio      float  %6.2f                  Gear Ratio
foreign         byte   %8.0g       origin     Car type
--------------------------------------------------------------------------------
Sorted by:  foreign
```

It is sorted by `foreign` (2 values), but has 74 observations. *So*. . .

Generating a new ID variable using `sencode`

...we then use `sencode`, with the `gsort()` option, to generate a new factor variable `make2`, ordered by descending weight. Then, we sort the dataset by this new ID variable:

```
. sencode make, gsort(-weight) generate(make2);

. describe make2;

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------
make2           byte   %17.0g      make2      Make and Model

. keyby make2;
```

The `keyby` package can be downloaded from SSC. It is an extension of `sort`, and checks that the sort key variables uniquely identify the observations, and moves the key variables to the start of the variable order (unless the user specifies the `noorder` option).

The new improved `auto` dataset

We now `describe` the improved `auto` dataset:

```
. describe;

Contains data from C:\Program Files (x86)\Stata12\ado\base/a/auto.dta
  obs:            74                          1978 Automobile Data
 vars:            13                          13 Apr 2011 17:45
 size:         3,256                          (_dta has notes)
--------------------------------------------------------------------------------
              storage  display     value
variable name   type   format      label      variable label
--------------------------------------------------------------------------------
make2           byte   %17.0g      make2      Make and Model
make            str18  %-18s                  Make and Model
price           int    %8.0gc                 Price
mpg             int    %8.0g                  Mileage (mpg)
rep78           int    %8.0g                  Repair Record 1978
headroom        float  %6.1f                  Headroom (in.)
trunk           int    %8.0g                  Trunk space (cu. ft.)
weight          int    %8.0gc                 Weight (lbs.)
length          int    %8.0g                  Length (in.)
turn            int    %8.0g                  Turn Circle (ft.)
displacement    int    %8.0g                  Displacement (cu. in.)
gear_ratio      float  %6.2f                  Gear Ratio
foreign         byte   %8.0g       origin     Car type
--------------------------------------------------------------------------------
Sorted by:  make2
     Note:  dataset has changed since last saved
```

The dataset is now sorted (and keyed) by the new labelled numeric ID variable `make2`, which is now the first variable. *However*. . .

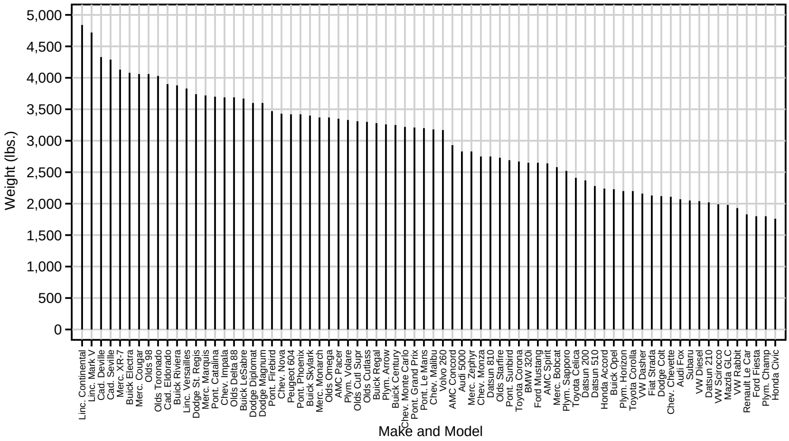
Using a `sencode` output factor on a graph axis

. . . to see what this new factor looks like, we use it to make a spike graph of car weights, using `twoway spike`:

```
. twoway spike weight make2,
>   ylabel(0(500)5000)
>   xlabel(1(1)74, labsize(2) angle(90))
>   xsize(6.5) ysize(3.75);
```

(Note that we could not have done this with the original string variable `make`.)

Weights of cars in the `auto` dataset



The models are ordered by descending weight, with the very few tied weights broken alphabetically.

Producing subset plots by decoding and re–encoding

- We often want to plot subsets of a dataset.
- *For instance*, we might want to produce a version of the previous plot, restricted to cars costing at least 9,000 1978 US dollars.
- When we do this, it often makes sense to decode the factor to string for the subset (using `sdecode`), and then to encode it back (using `sencode`).
- `sdecode`ing and `sencode`ing back is a commonly–used trick, as we shall see later.

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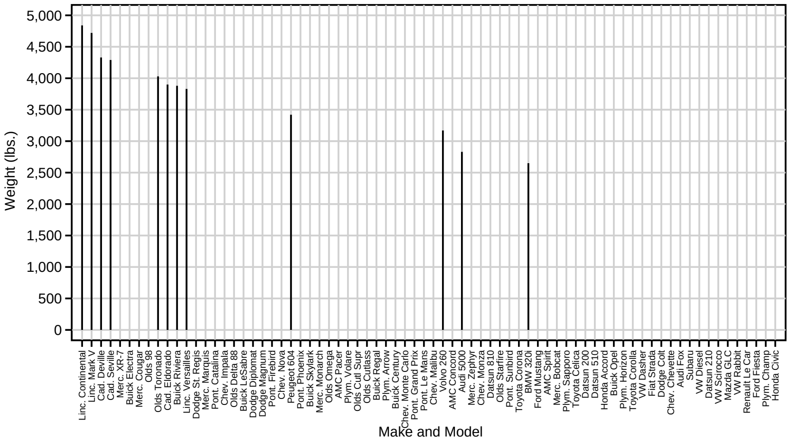
How do we make our subset plot? (Take 1)

We might be tempted to repeat the previous `twoway spike` command, adding only an `if` qualifier, as follows:

```
. twoway spike weight make2 if price>=9000,
>   ylabel(0(500)5000)
>   xlabel(1(1)74, labsize(2) angle(90))
>   xsize(6.5) ysize(3.75);
```

This might seem sensible at first. *However*. . .

Weights of cars costing at least 9,000 US dollars (take 1)



. . .this is not the graph we really wanted. The subset *X*–labels are unevenly spaced, and unwanted models are still listed, because the cars are still numbered as before. So what *should* we have done?

How do we make our subset plot? (Take 2)

A better way is to decode `make2`, with the `if` qualifier, to a string variable `make3`, and to encode `make3` back to numeric with the same ordering. This method has the added advantage that we can *italicize* the axis labels, using the `prefix()` and `suffix()` options of `sdecode` to add SMCL prefixes and suffixes:

```
. sdecode make2 if price>=9000, generate(make3) prefix("{it:") suffix("}");

. sencode make3, replace gsort(make2);

. describe make2 make3;

              storage  display     value
variable name   type   format      label      variable label
------------------------------------------------------------------------------------------------
make2           byte   %17.0g      make2      Make and Model
make3           byte   %22.0g      make3      Make and Model
```

We now have 2 factor variables with different value labels.

How do we make our subset plot? (Take 2, continued)

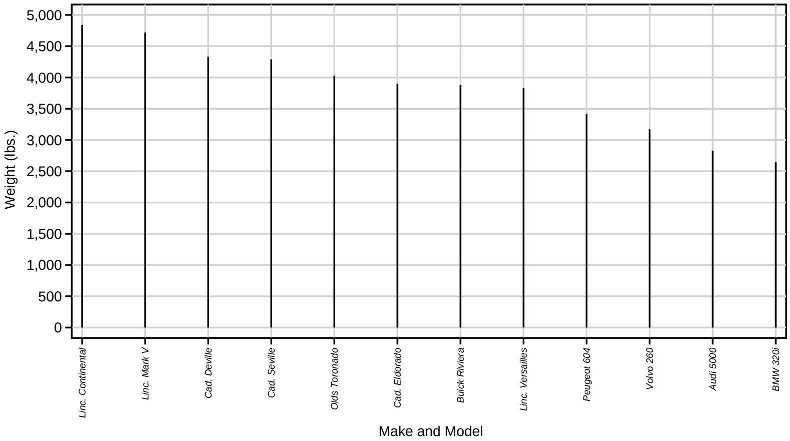
And, this time, when we make the plot, we use `levelsof` to extract the list of values of `make3` to a local macro `xlabs`, and use this macro to specify the *X*–axis labels for our `twoway spike` graph:

```
. levelsof make3, local(xlabs);
1 2 3 4 5 6 7 8 9 10 11 12

. twoway spike weight make3,
>   ylabel(0(500)5000)
>   xlabel(`xlabs', labsize(2) angle(90))
>   xsize(6.5) ysize(3.75);
```

So what does this graph look like?

Weights of cars costing at least 9,000 US dollars (take 2)



This looks more like the graph we wanted. The *X*–axis labels are now subsetted, evenly spaced *and* italicized.

Bringing order to concatenated resultssets

- A **resultsset** is a Stata dataset produced as output by a Stata command, such as the ones in the SSC package `parmest`[1].
- These resultssets are frequently **concatenated**, using `append`, especially when we make multiple resultssets containing parameter estimates from multiple model fits.
- And they often contain a **string ID variable**, specified by the `idstr()` option, identifying which resultsset an observation came from.
- In the concatenated resultsset, we usually use `sencode` to extract numeric factors from the string ID variable.
- These factors are then used for sorting and/or plotting the concatenated resultsset.

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Code to produce a concatenated resultsset in the `auto` dataset

This alien–looking code (which you do *not* need to memorize) uses the `parmby` module of the `parmest` package to fit unadjusted and weight–adjusted regression models of `mpg` with respect to `foreign`, with confidence limits from the unequal–variance and equal–variance formulas. The parameters from these 4 estimations are saved in 4 temporary `parmby` resultssets, identified using the `idstr()` option, which are then concatenated into the memory using `append`, after the old dataset has been cleared:

```
tempfile tf1 tf2 tf3 tf4;
parmby "regress mpg foreign, vce(robust)",
  idstr("Unequal&Unadjusted") saving(`"`tf1'"', replace);
parmby "regress mpg foreign weight, vce(robust)",
  idstr("Unequal&Adjusted") saving(`"`tf2'"', replace);
parmby "regress mpg foreign",
  idstr("Equal&Unadjusted") saving(`"`tf3'"', replace);
parmby "regress mpg foreign weight",
  idstr("Equal&Adjusted") saving(`"`tf4'"', replace);
clear all;
append using `"`tf1'"' `"`tf2'"' `"`tf3'"' `"`tf4'"';
```

Variables in the concatenated resultsset

When we `describe` the concatenated resultsset, we see that it contains parameter estimates, confidence limits and *P*–values:

```
. describe;

Contains data
  obs:            10
 vars:            10
 size:           750
--------------------------------------------------------------------------------------
              storage  display     value
variable name   type   format      label      variable label
--------------------------------------------------------------------------------------
parmseq         byte   %12.0g                 Parameter sequence number
idstr           str18  %18s                   String ID
parm            str7   %9s                    Parameter name
estimate        double %10.0g                 Parameter estimate
stderr          double %10.0g                 SE of parameter estimate
dof             byte   %10.0g                 Degrees of freedom
t               double %10.0g                 t-test statistic
p               double %10.0g                 P-value
min95           double %10.0g                 Lower 95% confidence limit
max95           double %10.0g                 Upper 95% confidence limit
--------------------------------------------------------------------------------------
Sorted by:
     Note:  dataset has changed since last saved
```

However, this resultsset does not seem to be sorted by anything!

Confidence intervals in the concatenated resultsset

When we `list` the concatenated resultsset, there seems to be more hope of some order being established:

```
. list idstr parmseq parm estimate min* max*, sepby(idstr);

     +---------------------------------------------------------------------------------+
     |               idstr   parmseq      parm     estimate        min95         max95 |
     |---------------------------------------------------------------------------------|
  1. | Unequal&Unadjusted          1   foreign    4.9458042    1.8670625     8.0245459 |
  2. | Unequal&Unadjusted          2     _cons    19.826923    18.510426      21.14342 |
     |---------------------------------------------------------------------------------|
  3. |   Unequal&Adjusted          1   foreign   -1.6500291   -3.9083006      .6082424 |
  4. |   Unequal&Adjusted          2    weight   -.00658789   -.00767698    -.00549879 |
  5. |   Unequal&Adjusted          3     _cons    41.679702    38.095484      45.26392 |
     |---------------------------------------------------------------------------------|
  6. |   Equal&Unadjusted          1   foreign    4.9458042    2.2303837     7.6612247 |
  7. |   Equal&Unadjusted          2     _cons    19.826923    18.346341     21.307505 |
     |---------------------------------------------------------------------------------|
  8. |     Equal&Adjusted          1   foreign   -1.6500291   -3.7955004     .49544223 |
  9. |     Equal&Adjusted          2    weight   -.00658789   -.00785825    -.00531752 |
 10. |     Equal&Adjusted          3     _cons    41.679702    37.361724     45.997681 |
     +---------------------------------------------------------------------------------+
```

The string ID variable `idstr` identifies the 4 estimations, and the numeric variable `parmseq` gives the parameter sequence order within each estimation.

Bringing order to the concatenated resultsset

This is done using the `split` command to split the string ID variable (at the ampersand) into 2 new string variables (`S_1` and `S_2`), and then using `sencode` to encode them to 2 numeric variables (`vartype` and `adjtype`), which are given variable labels and used to key the resultsset, after the old string variables have been `drop`ped:

```
. split idstr, parse(&) generate(S_);
variables created as string:
S_1  S_2

. sencode S_1, gene(vartype);

. sencode S_2, gene(adjtype);

. lab var vartype "Variance type";

. lab var adjtype "Adjustment type";

. drop idstr S_*;

. keyby vartype adjtype parmseq;
```

Note that `sencode` encodes string values in order of appearance, if no `gsort()` option is specified.

Variables in the improved concatenated resultsset

These are now as follows:

```
. describe;

Contains data
  obs:            10
 vars:            11
 size:           590
-------------------------------------------------------------------------------------
              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------------
vartype         byte   %8.0g       vartype    Variance type
adjtype         byte   %10.0g      adjtype    Adjustment type
parmseq         byte   %12.0g                 Parameter sequence number
parm            str7   %9s                    Parameter name
estimate        double %10.0g                 Parameter estimate
stderr          double %10.0g                 SE of parameter estimate
dof             byte   %10.0g                 Degrees of freedom
t               double %10.0g                 t-test statistic
p               double %10.0g                 P-value
min95           double %10.0g                 Lower 95% confidence limit
max95           double %10.0g                 Upper 95% confidence limit
-------------------------------------------------------------------------------------
Sorted by:  vartype  adjtype  parmseq
     Note:  dataset has changed since last saved
```

This resultsset is sorted (and keyed) by 3 numeric variables.

Confidence intervals in the improved concatenated resultsset

The dataset also looks better when listed (key variables first)...

```
. list vartype adjtype parmseq parm estimate min* max*, sepby(vartype adjtype);

     +---------------------------------------------------------------------------------+
     | vartype      adjtype   parmseq      parm     estimate        min95        max95 |
     |---------------------------------------------------------------------------------|
  1. | Unequal   Unadjusted         1   foreign    4.9458042    1.8670625    8.0245459 |
  2. | Unequal   Unadjusted         2     _cons    19.826923    18.510426     21.14342 |
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 10. |   Equal     Adjusted         3     _cons    41.679702    37.361724    45.997681 |
     +---------------------------------------------------------------------------------+
```
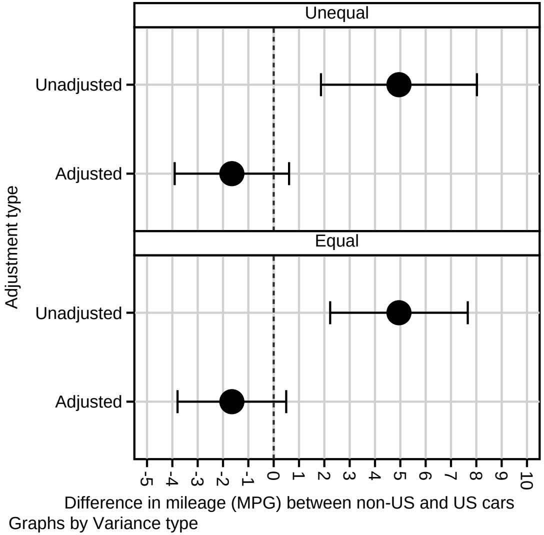

Mileage differences between non–US and US cars (plotted using the SSC package `eclplot`)

- . . .and better still when we plot only the `foreign` effects.
- We see that non–US cars do more miles per gallon than US cars.
- *However*, this difference vanishes after adjusting for weight.
- Of course, `split` and `sencode` can extract more than 2 factors from the same string ID.



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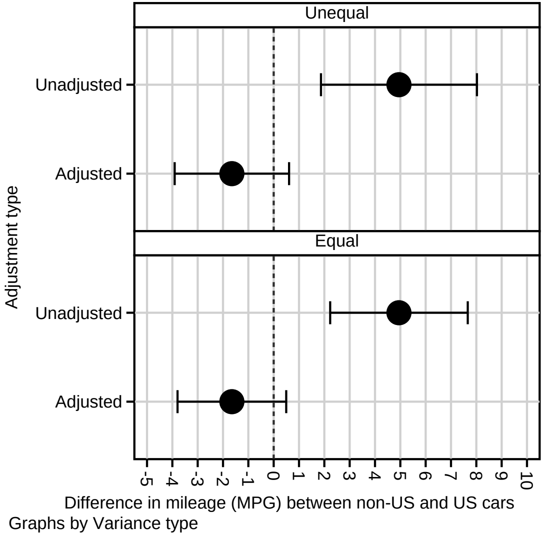

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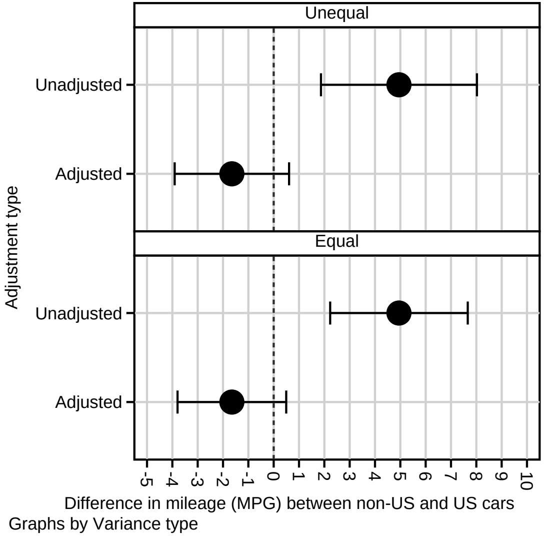

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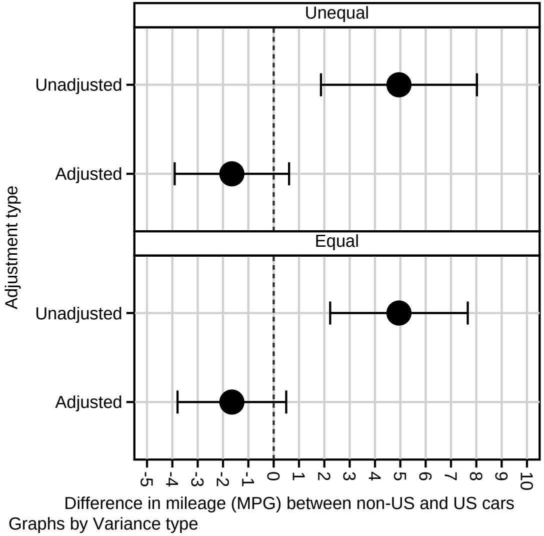

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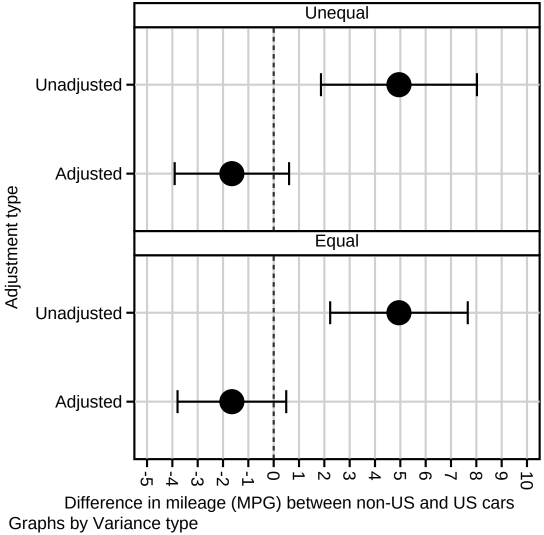
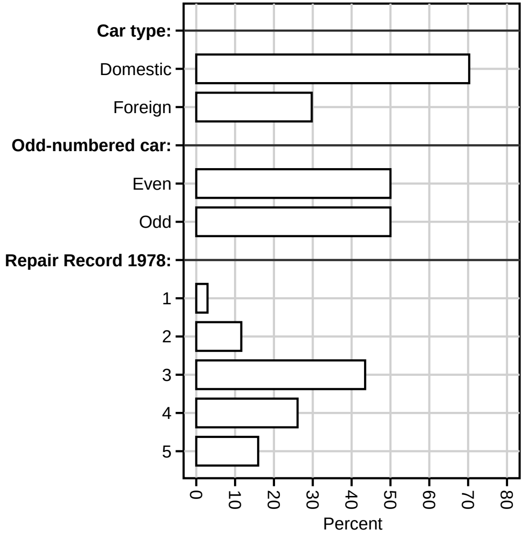


Advanced example: Frequency distributions of 3 factors in the `auto` dataset

- This histogram describes the distributions of 3 factors, with different levels and numbers of levels.
- These factors are `foreign`, `rep78`, and the added factor `odd=mod(_n,2)`.
- So how do we produce a multi–factor histogram like this?



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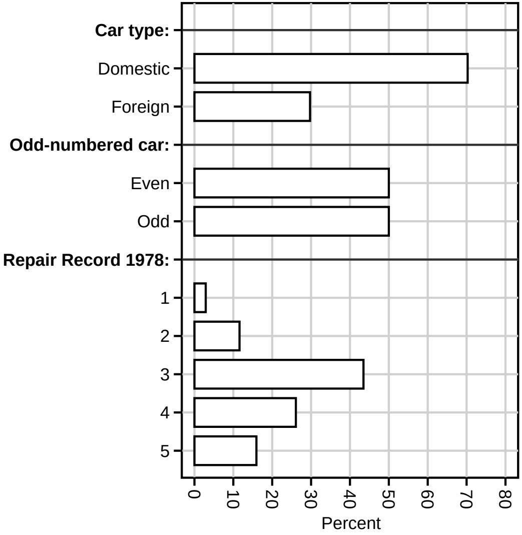

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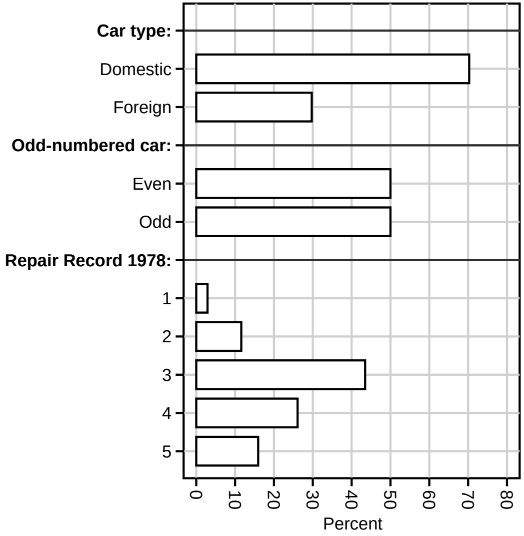

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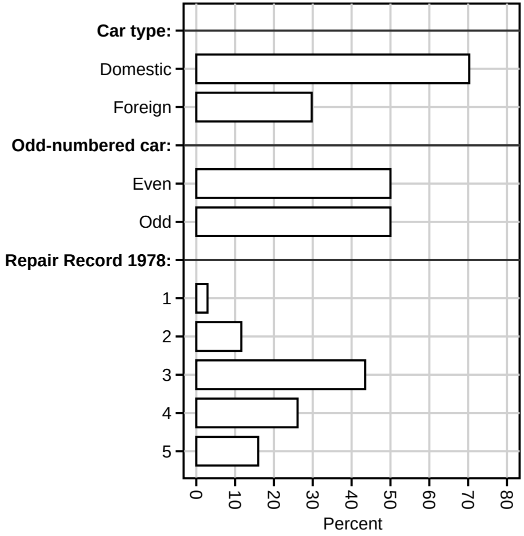

Creating the multi–factor histogram using `sdecode` and `sencode` (repeatedly)

- We start by using the SSC package `xcontract` (an extended version of `contract`) to make 3 frequency resultssets, one for each factor, which we `append` into the memory.
- We then replace these 3 old factors with 2 new key factors, indicating the old factors and the old–factor levels, respectively.
- We then replace the 2 new key factors with a single key factor, which we plot against the variable `_percent` to make the histogram.
- This kind of destructive mutilation of resultssets is usually done in a do–file, between a `preserve` statement and a `restore` statement. (*Not* interactively.)

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The first concatenated resultsset (with 3 key factors)

This was made by `append`ing 3 `xcontract` resultssets (one for each factor). It has 3 factors, 1 observation per level per factor, and a lot of missing factor values.

```
. list, sepa(0);

     +-----------------------------------------------+
     |  foreign    odd   rep78   _freq   _percent |
     |-----------------------------------------------|
  1. | Domestic      .       .      52      70.27 |
  2. |  Foreign      .       .      22      29.73 |
  3. |        .   Even       .      37      50.00 |
  4. |        .    Odd       .      37      50.00 |
  5. |        .      .       1       2       2.90 |
  6. |        .      .       2       8      11.59 |
  7. |        .      .       3      30      43.48 |
  8. |        .      .       4      18      26.09 |
  9. |        .      .       5      11      15.94 |
     +-----------------------------------------------+
```

The second concatenated resultsset (with 2 key factors)

This was made by replacing the 3 factors with 2 factors, `factor` and `faclev`, created by the decoding–encoding command sequence:

```
factmerg foreign odd rep78, flabel(factor) fvalue(faclev);
sencode factor, replace;
sencode faclev, replace manyto1 gsort(factor foreign odd rep78);
```

It still has 1 observation per level per factor. *However*, it is slimmer, with no missing factor values.

```
. list, sepby(factor);

     +---------------------------------------------------+
     |            factor     faclev   _freq   _percent |
     |---------------------------------------------------|
  1. |          Car type   Domestic      52      70.27 |
  2. |          Car type    Foreign      22      29.73 |
     |---------------------------------------------------|
  3. |   Odd-numbered car       Even      37      50.00 |
  4. |   Odd-numbered car        Odd      37      50.00 |
     |---------------------------------------------------|
  5. | Repair Record 1978          1       2       2.90 |
  6. | Repair Record 1978          2       8      11.59 |
  7. | Repair Record 1978          3      30      43.48 |
  8. | Repair Record 1978          4      18      26.09 |
  9. | Repair Record 1978          5      11      15.94 |
     +---------------------------------------------------+
```

The third concatenated resultsset (with 1 key factor)

This was made by replacing the 2 factors with 1 factor `row`, created by the decoding–encoding command sequence:

```
sdecode faclev, gene(row);
insingap factor, rowlabel(row) grdecode(factor) inner(faclev)
  neworder(rowseq1) gapindicator(gapstat) prefix("{bf:") suffix(":}");
sencode row, replace manyto1;
```

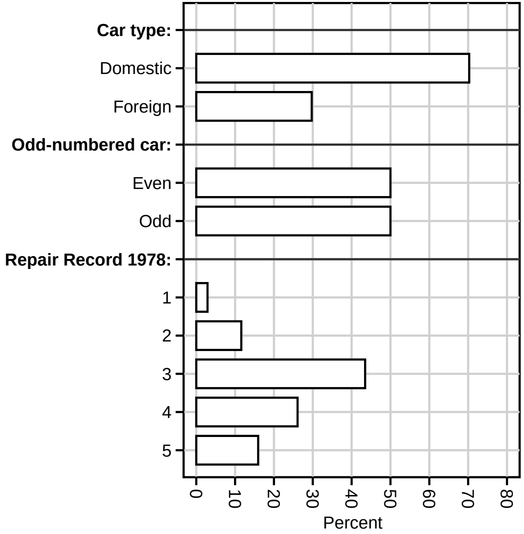
It is even slimmer, taller, and richer, with added SMCL **gap observations**, introducing each of the 3 original factors. *So*, it now has 1 observation per row of the planned multi–factor histogram. . .

```
. list row _freq _percent, sepby(factor);

     +-----------------------------------------------+
     |                        row   _freq   _percent |
     |-----------------------------------------------|
  1. |            {bf:Car type:}       .          . |
  2. |                  Domestic      52      70.27 |
  3. |                   Foreign      22      29.73 |
     |-----------------------------------------------|
  4. |    {bf:Odd-numbered car:}       .          . |
  5. |                      Even      37      50.00 |
  6. |                       Odd      37      50.00 |
     |-----------------------------------------------|
  7. |  {bf:Repair Record 1978:}       .          . |
  8. |                         1       2       2.90 |
  9. |                         2       8      11.59 |
 10. |                         3      30      43.48 |
 11. |                         4      18      26.09 |
 12. |                         5      11      15.94 |
     +-----------------------------------------------+
```

Frequency distributions of 3 factors in the `auto` dataset

- ...which we then create using a `twoway bar` command, plotting `_percent` against `row`.
- Note that each factor has a bold–font heading, made using SMCL.
- Similar decoding and encoding sequences can be used to produce TEX, HTML or RTF tables[3].



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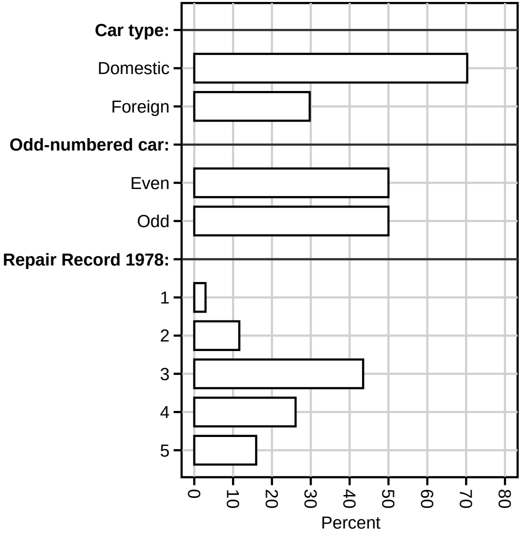

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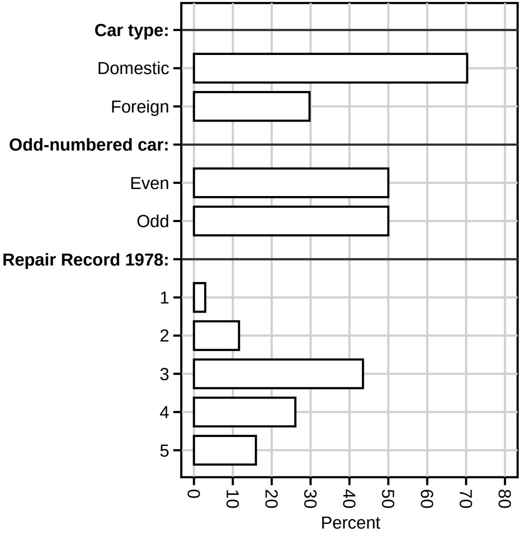

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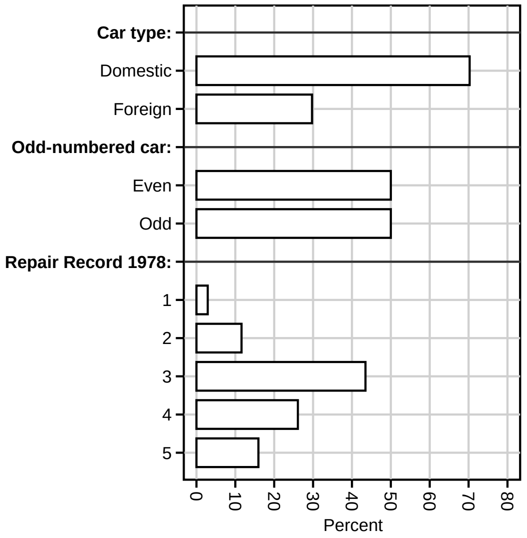
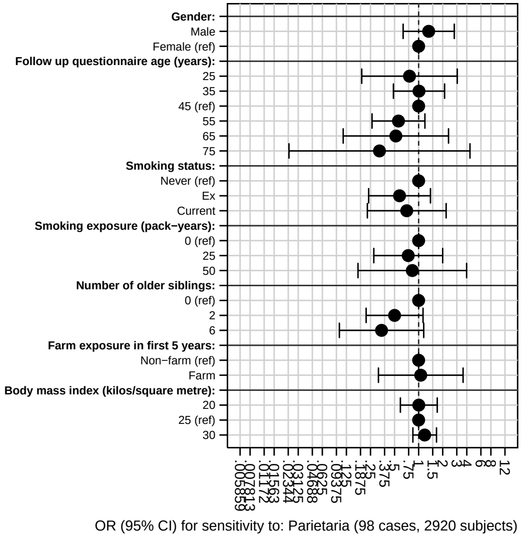


Odds ratios for *Parietaria* pollen allergy in the GA^{2}LEN survey

- And similar tricks also work with factors regenerated in `parmest` resultssets, using `fvregen`[2] and `factext`[1].
- In the GA^{2}LEN survey, we fitted multi–factor logistic models, predicting skin–prick allergies using discrete and continuous factors.
- Continuous factors were modelled using additive reference splines[4].



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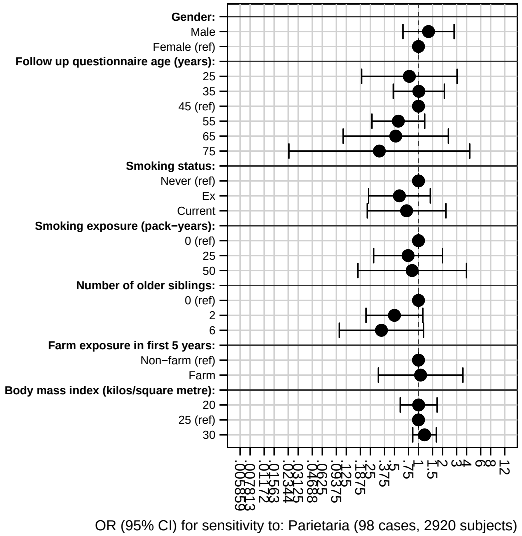

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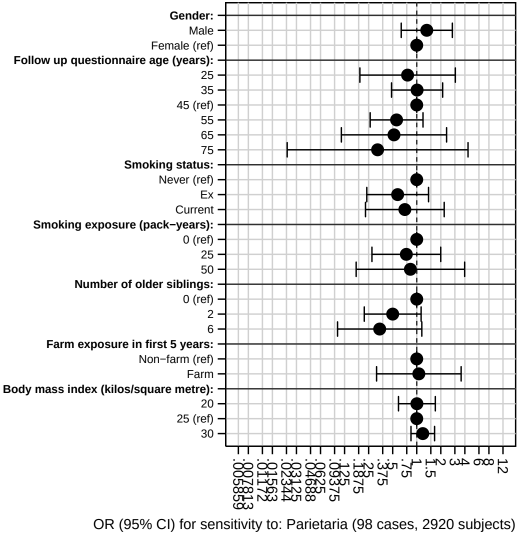

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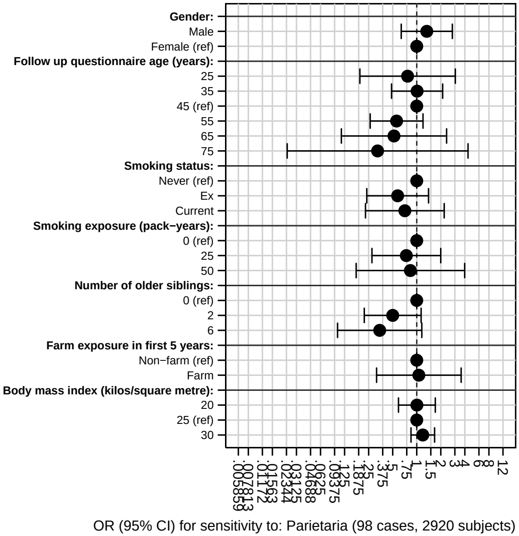

References

[1] Newson, R. 2004. From datasets to resultssets in Stata. Presented at the *10th UK Stata User Meeting*, 28–29 June, 2004. Downloadable from the conference website at *http://ideas.repec.org/s/boc/usug04.html*

[2] Newson, R. B. 2010. Post–`parmest` peripherals: `fvregen`, `invcise`, and `qqvalue`. . Presented at the *16th UK Stata User Meeting*, 9–10 September, 2010. Downloadable from the conference website at *http://ideas.repec.org/s/boc/usug10.html*

[3] Newson, R. B. 2012. From resultssets to resultstables in Stata. *The Stata Journal* **12(2)**: 479–504.

[4] Newson, R. B. 2012. Sensible parameters for univariate and multivariate splines. *The Stata Journal* **12(3)**: 479–504.

This presentation, and the do–file producing the examples in the `auto` data, can be downloaded from the conference website at *http://ideas.repec.org/s/boc/usug13.html*

The packages used in this presentation can be downloaded from SSC, using the `ssc` command.