f_able: Estimation of marginal effects with transformed covariates

Taking Margins a step further

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Introduction

- Marginal effects tells us how a dependent variable (outcome) y changes when an independent variable x changes, assuming everything else constant (e and z's).

$$y = b_0 + b_1 x + b_2 z + e$$

- For linear models, with no interactions or polynomials, marginal effects are equal to their coefficients:

$$\frac{dy}{dx} = b_1 \& \frac{dy}{dz} = b_2$$

- However, when there are interactions, polynomials, or other transformations, further work is needed.

Estimating Marginal effects

- When interactions or polynomials are used, marginal effects should be obtained estimating equation derivatives:

$$y = b_0 + b_1 x + b_2 x^2 + b_3 z + b_4 zx + e$$

$$\frac{dy}{dx} = b_1 + 2b_2 x + b_4 z$$

$$\frac{dy}{dz} = b_3 + b_4 x$$

- Main difference with simple linear model?
  - Marginal effects no longer constant
  - Coefficients alone are not useful
  - Derivatives are needed to obtain the effects.

Estimating Marginal effects: Non-linear model

- When the model is nonlinear, the problem is :

$$y = G(b_0 + b_1 x + b_2 x^2 + b_3 z + b_4 zx)$$

$$y = G(XB)$$

$$\frac{dy}{dx} = \frac{dG(XB)}{d(XB)} * (b_1 + 2b_2 x + b_4 z)$$

- In Addition to obtaining derivatives of XB wrt x, we also need to find the derivative of $G()$ wrt XB

Estimating Marginal effects

How to proceed in this case? what to report? There are many options:

$$APE = E\left(\frac{dy}{dx}\right)$$

$$PEA = \frac{dy}{dx}|X = \bar{x}; z = \bar{z}$$

$$PE\_at\_X = \frac{dy}{dx}|X = X; z = Z$$

Or report "ALL" effects for each observation in the data.
Then "simply" estimate SE.

Empirical Estimation of Marginal effects

- Before Stata 11, estimation of marginal effects for models with interactions was "hard".
- You needed to create the variables "by hand", and adjust marginal effects on your own:

```
. webuse dui, clear
. gen fines2=fines*fines
. reg citations fines fines2
. sum fines2
. lincom _b[fines]+2*_b[fines2]*`r(mean)'
```

- Otherwise, using the old -mfx- or the new -margins- would give you incorrect results.
- why? because Stata does not recognize that $fines2 = fines^2$. Fines2 is assumed constant.

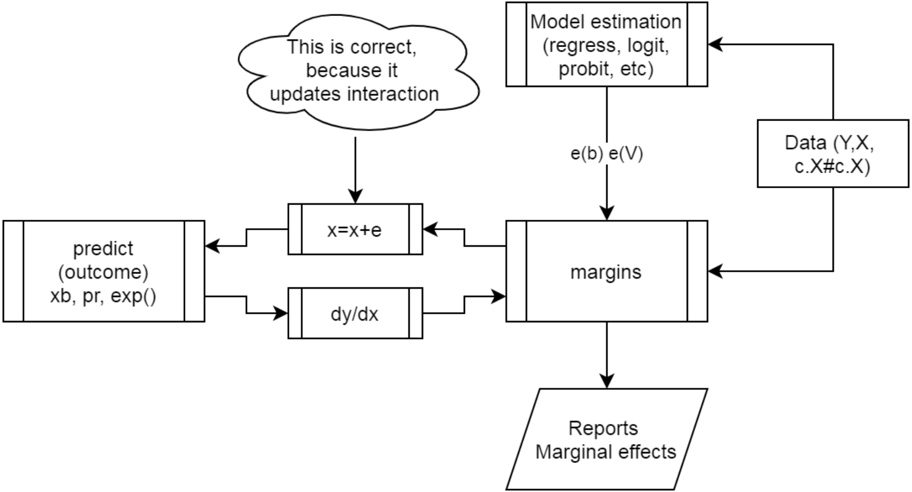
Margins and Factor notation, and limitations

- Stata 11 introduced the use of factor notation, and margins.
- Factor notation (c. # i.) facilitates adding interactions to models, so that correct marginal effects can be estimated using `margins`
- Marginal effects for the previous model can be easily estimated:

```
. webuse dui, clear
. reg citations fines c.fines#c.fines
(where c.fines#c.fines=fines^2)
. margins, dydx(fines)
```

- Internally, `margins` understand c.fines#c.fines depends on fines. (And probably estimates analytical derivatives to obtain the PE).
- when nonlinear models are involved `margins` calls on `predict` if one is interested on an outcome different from the linear index.

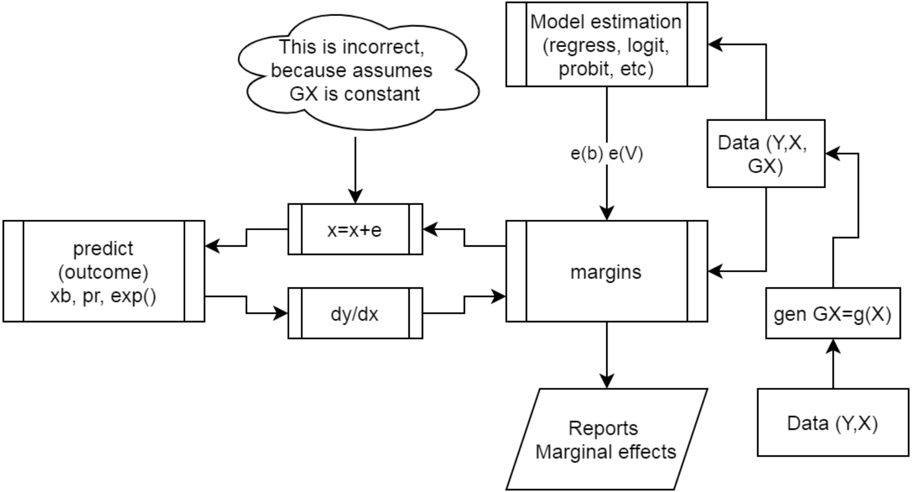
How `margins` Works?



Limitations of `margins`

- What If one is interested in using other variable transformations, for example: $fines^{.5}$, $log(fines)$, *splines*, *fracpoly*, etc
- In any of these cases, `margins` will not work.
- why? Because these variables will have to be created manually, and Margin will not recognized they all depend on fines.
- One solution, estimate the derivatives manually, and calculate corresponding SE.
- Same as before factor notation.

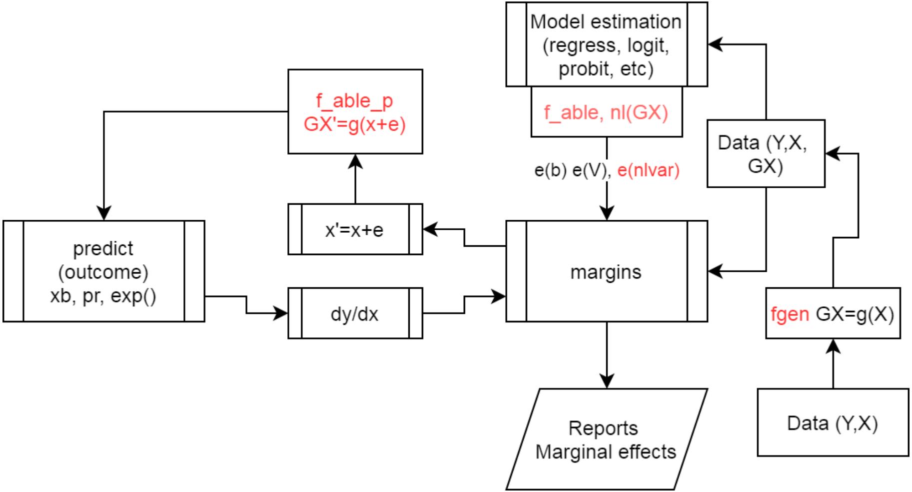
Why does it fail?



Beyond factor notation

- Some other commands in Stata are already able to control for "unusual" variable transformations (`nl` and `npregress series`).
- However, for any command being able to use those capabilities, one needs to solve three problems:
  - Store information of how a variable is created.
  - Identify that a variable is a constructed variable.
  - Use that information to update constructed variables, and obtain partial effects.
- Here is where `f_able` helps solving these problems.

How does `f_able` works?



f_able package: fgen and frep

- To solve the first problem, I propose `fgen` and `frep`. These commands are wrappers around `generate` and `replace` that stores how the variable was generated, as a label or note.

```
. ssc install f_able
. qui:fgen fines2=fines^2
. describe fines2
              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------
fines2          double  %10.0g                fines^2

. qui:frep fines2=fines*fines
. describe fines2
              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------
fines2          double  %10.0g                fines*fines
```

f_able package: f_able

- To solve the second problem, I propose `f_able`. This is a post estimation command that identifies what variables in a model are "constructed" variables, adding information to any previously estimated model, and redirecting the `predict` sub-command to `f_able_p`.

```
. qui:reg citations fines fines2
. f_able, nl(fines2)
. ereturn list, all
scalars: (omitted)
macros: (other macros omitted)
           e(nldepvar) : "fines2"
            e(predict) : "f_able_p"
        e(predict_old) : "regres_p"
Hidden macros: (other hidden macros omitted)
            e(_fines2) : "fines*fines"
```

f_able package: f_able_p

- To solve the third problem, I propose `f_able_p`. This passive command uses the information left by `f_able` to update all constructed values when the original variable changes, before using predict for the margins estimation.
- Only difference, when calling `margins` we need to include the option `nochain`, so numerical derivatives are used.

```
. qui:reg citations fines fines2
. f_able, nl(fines2)
. margins, dydx(fines) nochain
Average marginal effects                        Number of obs     =        500
Model VCE     : OLS
Expression    : Fitted values, predict()
dy/dx w.r.t.  : fines
------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       fines |  -7.907201   .4236816   -18.66   0.000    -8.737602     -7.0768
------------------------------------------------------------------------------
```

f_able syntax

```
* Step 1: Generate variables
fgen/frep fx1= "gen-able" function of x's
fgen/frep fx2= "gen-able" function of x's
fgen/frep fxk= "gen-able" function of x's

* Step 2: Model estimation: Any model

* Step 3: Declare constructed variables:
f_able, nl(fx1 fx2 ... fxk)

* Step 4: Margins
margins, dydx(x1 x2 ..) nochain numerical [other options]

* Step 5: Additional post estimation (if no standard errors produced)
f_symev/f_symrv
```

Example:A model of Charity

```
use charity, clear
fgen lavggift=log(avggift)
fgen lweekslast=log(weekslast)
fgen lmailsyear=log(mailsyear)
fgen lpropresp=log(propresp)

*Simple OLS
reg gift resplast weekslast mailsyear propresp avggift , robust
margins, dydx(resplast weekslast mailsyear propresp avggift) post
est sto model1

*OLS with LOG(Var)
reg gift resplast weekslast mailsyear propresp avggift l*, robust
f_able, nl(lavggift lweekslast lmailsyear lpropresp)
margins, dydx(resplast weekslast mailsyear propresp avggift) nochain post
est sto model2
```

Example:A model of Charity

```
*Poisson with LOG(var)
poisson gift resplast weekslast mailsyear propresp avggift l*, robust
f_able, nl(lavggift lweekslast lmailsyear lpropresp)
margins, dydx(resplast weekslast mailsyear propresp avggift) ///
nochain numerical post
est sto model3

*Tobit with LOG(var)
tobit gift resplast weekslast mailsyear propresp avggift l*, vce(robust) ll(0)
f_able, nl(lavggift lweekslast lmailsyear lpropresp)
margins, dydx(resplast weekslast mailsyear propresp avggift) ///
nochain  numerical predict(ystar(0,.)) post
est sto model4
```

Example:A model of Charity

```
. esttab model1 model2 model3 model4, mtitle("S OLS" "OLS w/Logs" "Poisson" "Tobit") ///
se star(* .1 ** .05 *** .01)
----------------------------------------------------------------------------
                      (1)             (2)             (3)             (4)
                    S OLS      OLS w/Logs         Poisson           Tobit
----------------------------------------------------------------------------
resplast            1.514**         3.527***        2.743***        3.094***
                  (0.719)         (0.990)         (0.634)         (0.605)
weekslast         -0.0186***       0.0755***        0.105***       0.0953***
                (0.00590)        (0.0212)        (0.0178)        (0.0182)
mailsyear           1.992***        0.605           1.241***        0.913***
                  (0.396)         (0.464)         (0.339)         (0.309)
propresp            11.64***        15.67***        11.08***        14.12***
                  (1.283)         (1.942)         (1.224)         (1.170)
avggift            0.0199           0.847***        0.437***        0.394***
                 (0.0176)        (0.0753)        (0.0198)        (0.0327)
----------------------------------------------------------------------------
N                    4268            4268            4268            4268
----------------------------------------------------------------------------
Standard errors in parentheses
* p<.1, ** p<.05, *** p<.01
```

Conclusions

- This presentation introduces the package `f_able`, as a post estimation command that enables `margins` to estimate marginal effects with transformed covariates
- This strategy has some limitations.
  - It can be slow
  - it may be less precise because it relies on FORCED numerical differentiation.
  - Some commands may require additional "margin" options (nochain & numerical) and post estimation adjustment.
- However, it can provide researchers with a simple tool to make the best of more flexible model specifications.

For more examples see the help file "ssc install f_able"
Working paper available at: https://bit.ly/rios_fable

Thank you!

References

Rios-Avila, Fernando. (forthcoming). "f_able: Estimation of marginal effects for models with alternative variable transformations". The Stata Journal