

Predictive Margins and Marginal Effects in Stata

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Outline

- Motivation
- margins and marginsplot
- regplot

Motivation

- For a long time, regression tables have been the preferred way of communicating results from statistical models.
- However, interpretation of regression tables can be very challenging in the case of interaction effects, categorical variables, or nonlinear functional forms.
- Moreover, interpretational difficulties can be overwhelming in nonlinear models such as logistic regression. In these models the raw coefficients are often not of much interest; what we want to see for interpretation are effects on outcomes such as probabilities, not on „latent“ variables such as log odds.
- Fortunately, Stata has a number of handy commands such as `margins`, `contrasts`, and `marginsplot` for making sense of regression results.

Example: Factorial Survey on Just Incomes

- Mail survey among a random sample of the Swiss population ($N = 1945$). Written questionnaire in German, French and Italian.
 - ▶ Data collected in fall 2010 as part of a follow-up survey to the “Swiss Environmental Survey 2007”
(see <http://www.socio.ethz.ch/research/umweltsurvey/umweltsurvey2007>)
- Respondents were asked to judge short text descriptions of (fictional) individuals (so called “vignettes”), in which certain elements are varied at random.
- For our research objective, we used vignettes describing men and women employing the following $2 \times 2 \times 2 \times 3$ design :
 - ▶ male vs. female
 - ▶ single without children vs. married without children
 - ▶ average work effort vs. above-average work effort
 - ▶ income levels: 5000 CHF, 5500 CHF, 6000 CHF

Example: The Vignette

In letzter Zeit wird viel über die Höhe von Löhnen in verschiedenen Berufen gesprochen. Wir interessieren uns für Ihre persönliche Einschätzung zu diesem Thema.

Stellen Sie sich die folgende Situation vor:

{Herr | Frau} Müller, 25-jährig, {allein stehend und ohne Kinder | verheiratet in kinderloser Ehe}, arbeitet als kaufmännische{r} Angestellte{r} im Rechnungswesen eines mittleren Dienstleistungsbetriebs und erbringt dort {überdurchschnittliche | durchschnittliche} Leistungen. {Sein | Ihr} monatliches Bruttoeinkommen beträgt {5'000 | 5'500 | 6'000} Franken.

Wie bewerten Sie das Einkommen dieser Person? Ist das Einkommen Ihrer Meinung nach gerecht oder ist es ungerechterweise zu hoch oder zu niedrig?

viel zu niedrig

gerecht

viel zu hoch

-5

-4

-3

-2

-1

0

+1

+2

+3

+4

+5

Example: The Data

```
. use vignettes  
(2010 Vignette Study on Just Incomes)
```

```
. d
```

Contains data from vignettes.dta

```
obs:      1,482      2010 Vignette Study on Just Incomes  
vars:      13        10 Jun 2013 11:16  
size:     51,870     (_dta has notes)
```

variable name	storage type	display format	value label	variable label
vrating	double	%13.0g	vrating	Vignette: rating (-5=much too low, 5=much too high)
vmale	byte	%8.0g	vmale	Vignette: male
vmarried	byte	%8.0g	vmarried	Vignette: married
veffort	byte	%25.0g	veffort	Vignette: above-average work effort
vinc	int	%10.0g	vinc	Vignette: income (CHF per month)
rmale	byte	%8.0g	rmale	Respondent: male
rage	byte	%8.0g	rage	Respondent: age
reducyr	double	%10.0g	reducyr	Respondent: years of education
rright	byte	%8.0g	rright	Respondent: political orientation (0=left, 10=right)
rmarstat	byte	%8.0g	rmarstat	Respondent: marital status
rinc	byte	%13.0g	rinc	Respondent: income (CHF per month)
wt	double	%10.0g	wt	sampling weights
strata	byte	%8.0g	strata	sampling strata

Sorted by:

Example: Analysis of the Vignette Data

- A simple linear regression model with the vignette responses as dependent variable – have fun interpreting!

```
. regress vrating vinc i.vmale i.vmarried i.veffort ///  
> vmale##rmale##c.reducyrs##c.reducyrs, vsquish noheader
```

vrating	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
vinc	.0010069	.000094	10.71	0.000	.0008225 .0011913
1.vmale	-1.388362	3.140572	-0.44	0.659	-7.548853 4.772129
1.vmarried	-.1799115	.0771521	-2.33	0.020	-.3312517 -.0285713
1.veffort	-.6662772	.0771985	-8.63	0.000	-.8177084 -.5148459
1.rmale	-.3799532	3.355975	-0.11	0.910	-6.962975 6.203068
vmale#rmale					
1 1	3.984662	4.818208	0.83	0.408	-5.46665 13.43597
reducyrs	.1051598	.3327842	0.32	0.752	-.5476238 .7579435
vmale#c.reducyrs					
1	.0722016	.4839479	0.15	0.881	-.877102 1.021505
rmale#c.reducyrs					
1	.0129762	.5123413	0.03	0.980	-.9920235 1.017976
vmale#rmale#c.reducyrs					
1 1	-.4443146	.7331748	-0.61	0.545	-1.882497 .9938681
c.reducyrs#c.reducyrs	-.0063593	.0123638	-0.51	0.607	-.030612 .0178933
vmale#c.reducyrs#c.reducyrs					
1	.0010164	.0178947	0.06	0.955	-.0340855 .0361183
rmale#c.reducyrs#c.reducyrs					
1	.0013596	.0187994	0.07	0.942	-.0355169 .0382361
vmale#rmale#c.reducyrs#c.reducyrs					
1 1	.0105725	.0268027	0.39	0.693	-.0420033 .0631482
_cons	-4.825754	2.224811	-2.17	0.030	-9.189904 -.4616041

Example: Analysis of the Vignette Data

- Questions we might have about the regression output:
 - ▶ What are the overall effects of the vignette factors?
 - ▶ How does the effect of vignette factor “sex” depend on education and sex of the respondent?
 - ▶ What is the shape of the effect of education depending on sex?
 - ▶ Can we express effects in CHF?

Example: Binary Dependent Variable

- A logistic regression of whether income in vignette was judged as “too low” or not:

```
. generate byte toolow = vrating<0 if vrating<.
. logit toolow vinc i.vmale i.vmarried i.veffort
```

```
Iteration 0:  log likelihood = -726.94882
Iteration 1:  log likelihood = -660.31413
Iteration 2:  log likelihood = -656.56237
Iteration 3:  log likelihood = -656.55323
Iteration 4:  log likelihood = -656.55323
```

```
Logistic regression                                Number of obs   =       1482
                                                    LR chi2(4)      =       140.79
                                                    Prob > chi2     =       0.0000
                                                    Pseudo R2      =       0.0968

Log likelihood = -656.55323
```

toolow	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
vinc	-.0013663	.0001789	-7.64	0.000	-.0017169	-.0010157
1.vmale	.3994001	.1393606	2.87	0.004	.1262584	.6725417
1.vmarried	.2886296	.1389959	2.08	0.038	.0162027	.5610565
1.veffort	1.164184	.1466717	7.94	0.000	.8767125	1.451655
_cons	4.939563	.9606374	5.14	0.000	3.056748	6.822378

Example: Binary Dependent Variable

- Questions we might have about the logit output:
 - ▶ What the hell do these coefficients mean?
 - ▶ What is the conditional probability of “too low” depending on different levels of the factor variables?
 - ▶ What is the marginal effect of the vignette factors on the probability of “too low”?

Stata tools to answer these questions

- Stata commands `margins` and `marginsplot` can help us answer these questions.
- There's another useful command called `contrast`, but I am not going to talk about that.
- However, I will also show `marginscontplot` by Patrick Royston that will appear in one of the next issues of the Stata Journal.

What can margins do?

- `margins` computes so-called margins of responses.
 - ▶ A “margin” is a statistic computed from predictions from a model while manipulating the values of the covariates.
 - ★ “conditional margin”: a prediction from a model where all covariates are set to fixed values
 - ★ “predictive margin”: if some covariates are not fixed
 - ▶ Computed are *levels* of margins for different covariate values or *differences* in levels of margins if covariate values are changed (or even differences in differences). The later is often called *marginal effects*.
 - ▶ Continuous vs. discrete marginal effects
 - ★ For a continuous covariate, `margins` computes the first derivative of the response with respect to the covariate.
 - ★ For a discrete covariate, `margins` computes the effect of a discrete change of the covariate (discrete change effects).
 - ▶ MEM: marginal effects at the mean, AME: average marginal effects, MER: marginal effects at representative values

Technical note

- You must use Stata's factor variable notation in the estimation command for `margins` to be able to compute correct results (see `help fvvarlist`).
 - ▶ Use the `i.` operator for discrete variables.
 - ▶ Use the `#` and `##` operators for interactions.
 - ▶ Use the `c.` for continuous variables involved in an interaction.

Answers: Overall effects of the vignette factors

- Predictive margins / adjusted predictions (levels)

```
. quietly regress vrating vinc i.vmale i.vmarried i.veffort ///  
>     vmale##rmale##c.reducyr##c.reducyr, vsquish noheader  
. margins vmale vmarried veffort
```

```
Predictive margins                                Number of obs   =           1482  
Model VCE      : OLS  
Expression     : Linear prediction, predict()
```

	Delta-method				[95% Conf. Interval]	
	Margin	Std. Err.	z	P> z		
vmale						
0	.5727241	.0541998	10.57	0.000	.4664945	.6789537
1	.2916397	.0547894	5.32	0.000	.1842544	.399025
vmarried						
0	.5250302	.054352	9.66	0.000	.4185023	.6315581
1	.3451187	.0546468	6.32	0.000	.238013	.4522245
veffort						
0	.7664507	.0543315	14.11	0.000	.6599629	.8729385
1	.1001736	.0547003	1.83	0.067	-.0070371	.2073843

Answers: Overall effects of the vignette factors

- Interpretation of predictive margins for `vma1e`:
 - ▶ If all respondents would have answered the *female* vignette (keeping the other vignette factors and the respondent's sex and education as they happen to be), then the average response would have been 0.57.
 - ▶ If all respondents would have answered the *male* vignette (keeping the other vignette factors and the respondent's sex and education as they happen to be), then the average response would have been 0.29.
 - ▶ This means that, keeping everything else constant, the same income is more likely to be judged as too low in the male vignette than in the female vignette.
 - ▶ To find out whether the difference is significant, we can use `margins` to compute contrasts or marginal effects.
 - ★ An alternative would be to specify the `post` option in the above command and then apply the `test` command (see below).

Answers: Overall effects of the vignette factors

- Contrasts (differences in levels): use the `r.` operator

```
. margins r.vmale r.vmarried r.veffort
```

```
Contrasts of predictive margins
```

```
Model VCE      : OLS
```

```
Expression     : Linear prediction, predict()
```

	df	chi2	P>chi2
vmale	1	13.30	0.0003
vmarried	1	5.44	0.0197
veffort	1	74.49	0.0000

	Contrast	Delta-method Std. Err.	[95% Conf. Interval]	
vmale (1 vs 0)	-.2810844	.0770733	-.4321454	-.1300234
vmarried (1 vs 0)	-.1799115	.0771521	-.3311268	-.0286961
veffort (1 vs 0)	-.6662772	.0771985	-.8175835	-.5149709

Answers: Overall effects of the vignette factors

- Marginal effects for discrete variables (discrete change effects): use the `dydx()` option

```
. margins, dydx(vmale vmarried veffort)
```

```
Average marginal effects          Number of obs   =          1482
```

```
Model VCE      : OLS
```

```
Expression    : Linear prediction, predict()
```

```
dy/dx w.r.t.  : 1.vmale 1.vmarried 1.veffort
```

	Delta-method				[95% Conf. Interval]	
	dy/dx	Std. Err.	z	P> z		
1.vmale	-.2810844	.0770733	-3.65	0.000	-.4321454	-.1300234
1.vmarried	-.1799115	.0771521	-2.33	0.020	-.3311268	-.0286961
1.veffort	-.6662772	.0771985	-8.63	0.000	-.8175835	-.5149709

Note: dy/dx for factor levels is the discrete change from the base level.

Answers: Overall effects of the vignette factors

- Interpretation contrasts / marginal effects
 - ▶ We see that both commands yield the same results.
 - ▶ The effect of male vs. female sex in the vignette is an average decrease of 0.28 points on the response scale. This is simply the difference in the predictive margins computed above.
 - ▶ The difference is highly significant with a z-value of 3.65 or a $\chi^2(1)$ -value of 13.3 (which is simply the square of the z-value because the test has 1 degree of freedom).
 - ▶ The 95% confidence interval of the effect is -0.43 to -0.13.

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- Let's start with the interaction with respondent's sex.
- Predictive margins for the vignette sex by sex of the respondent can be computed as follows:

```
. margins vmale, over(rmale)
```

```
Predictive margins                                Number of obs =      1482  
Model VCE      : OLS  
Expression     : Linear prediction, predict()  
over           : rmale
```

	Delta-method					
	Margin	Std. Err.	z	P> z	[95% Conf. Interval]	
rmale#vmale						
0 0	.580111	.0744694	7.79	0.000	.4341537	.7260683
0 1	.2069453	.0758263	2.73	0.006	.0583285	.3555621
1 0	.5645165	.0790644	7.14	0.000	.4095531	.7194799
1 1	.3857447	.0792884	4.87	0.000	.2303422	.5411472

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- We see that for female respondents, the difference in predictive margins for vignette sex is larger ($0.21 - 0.58 = -0.37$) than for male respondents ($0.39 - 0.56 = -0.17$).
 - ▶ Note that the difference could be due to differential educational levels of female and male respondents, because an interaction with education was included in the regression model and the predictive margins are averaged over female and male respondents as is. We could, for example, type

```
. margins vmale rmale, at((omean) reducyr)
```

to find out whether controlling for education changes the picture (it does a bit, but not much) (`omean` sets the respondent's education to the overall mean across all observations).
- To find out whether effects for female and males are significant we can again resort to the `r. contrast` operator or the `dydx()` option.

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- Using the `r.` contrast operator:

```
. margins r.vmale, over(rmale)
Contrasts of predictive margins
Model VCE      : OLS
Expression     : Linear prediction, predict()
over           : rmale
```

	df	chi2	P>chi2
vmale@rmale			
(1 vs 0) 0	1	12.32	0.0004
(1 vs 0) 1	1	2.55	0.1105
Joint	2	14.88	0.0006

	Delta-method		
	Contrast	Std. Err.	[95% Conf. Interval]
vmale@rmale			
(1 vs 0) 0	-.3731657	.1063105	-.5815304 -.164801
(1 vs 0) 1	-.1787718	.1120037	-.3982952 .0407515

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- Using the `dydx()` option:

```
. margins, dydx(vmale) over(rmale)
```

```
Average marginal effects          Number of obs   =       1482
Model VCE      : OLS
Expression    : Linear prediction, predict()
dy/dx w.r.t.  : 1.vmale
over          : rmale
```

		Delta-method				
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
1.vmale						
	rmale					
	0	-.3731657	.1063105	-3.51	0.000	-.5815304 -.164801
	1	-.1787718	.1120037	-1.60	0.110	-.3982952 .0407515

Note: dy/dx for factor levels is the discrete change from the base level.

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- Mechanics of the `over()` option:

- ▶ Specifying `over` is equivalent to running `margins` on subpopulations. That is, the results above could also be computed by typing

```
. margins if rmale==0, dydx(vmale)
. margins if rmale==1, dydx(vmale)
```

- ▶ Beware, however, that using `if` can lead to biased standard errors in complex samples. A safer approach is to use the `subpop()` option:

```
. margins, dydx(vmale) subpop(if rmale==0)
. margins, dydx(vmale) subpop(if rmale==1)
```

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- What we really want to know is whether the effect of the vignette sex is different for female respondents and for male respondents.
- We could test this, for example, as follows:

```
. estimates store lin
. margins, dydx(vmale) over(rmale) coeflegend post
Average marginal effects      Number of obs   =      1482
Model VCE      : OLS
Expression     : Linear prediction, predict()
dy/dx w.r.t.   : 1.vmale
over           : rmale
```

		dy/dx	Legend
1.vmale			
	rmale		
	0	-.3731657	_b[1.vmale:0bn.rmale]
	1	-.1787718	_b[1.vmale:1.rmale]

Note: dy/dx for factor levels is the discrete change from the base level.

```
. test _b[1.vmale:0bn.rmale] = _b[1.vmale:1.rmale]
( 1) [1.vmale]0bn.rmale - [1.vmale]1.rmale = 0
      chi2( 1) =    1.58
      Prob > chi2 =    0.2083

. est restore lin
(results lin are active now)
```


Answers: How does the effect of vignette sex depend on respondent's education and sex?

- A more direct approach is to have margins compute an estimate for the difference in differences by adding the `r.` operator within the `over()` option.
- Either type ...

```
. margins r.vmale, over(r.rmale)
Contrasts of predictive margins
Model VCE      : OLS
Expression    : Linear prediction, predict()
over          : rmale
```

	df	chi2	P>chi2
rmale#vmale	1	1.58	0.2083

	Delta-method		
	Contrast	Std. Err.	[95% Conf. Interval]
rmale#vmale (1 vs 0) (1 vs 0)	.1943939	.1544914	-.1084037 .4971914

Answers: How does the effect of vignette sex depend on respondent's education and sex?

- ... or type

```
. margins, dydx(vmale) over(r.rmale)
Contrasts of average marginal effects
Model VCE      : OLS
Expression    : Linear prediction, predict()
dy/dx w.r.t.  : 1.vmale
over          : rmale
```

	df	chi2	P>chi2
0b.vmale rmale	(omitted)		
1.vmale rmale	1	1.58	0.2083

	Contrast	Delta-method	[95% Conf. Interval]	
	dy/dx	Std. Err.		
1.vmale rmale (1 vs 0)	.1943939	.1544914	-.1084037	.4971914

Note: dy/dx for factor levels is the discrete change from the base level.

Answers: How does the effect of vignette sex depend on respondent's education and sex?

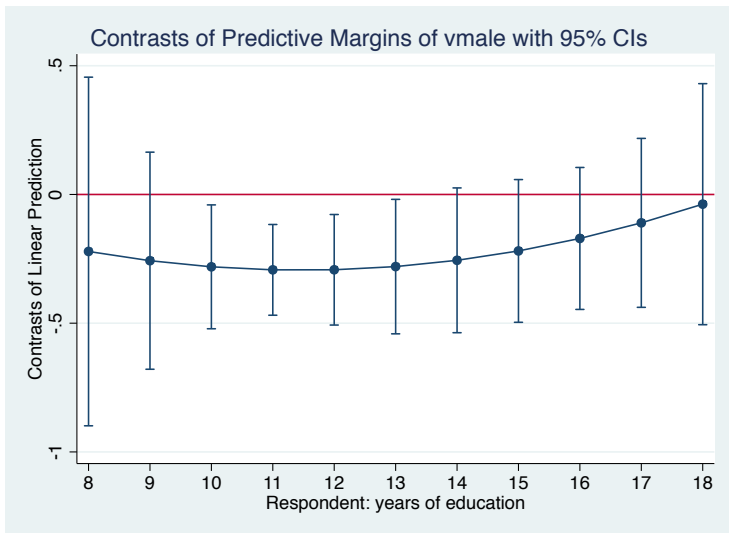
- Our conclusion from the above results would be that the effects of the vignette sex appears to be a bit stronger for female, but the difference is not significant.
- Again, note that there is a third variable involved in the interaction (education), so that part of the differences between the effects for female and male respondents might be due to different educational level.
- To see how the effect of the vignette sex changes by education, we could type

```
. margins r.vmale, at(reducyrs=(8(1)18))  
. marginsplot, yline(0)
```

or

```
. margins, dydx(vmale) at(reducyrs=(8(1)18))  
. marginsplot, yline(0)
```

Answers: How does the effect of vignette sex depend on respondent's education and sex?



Answers: How does the effect of vignette sex depend on respondent's education and sex?

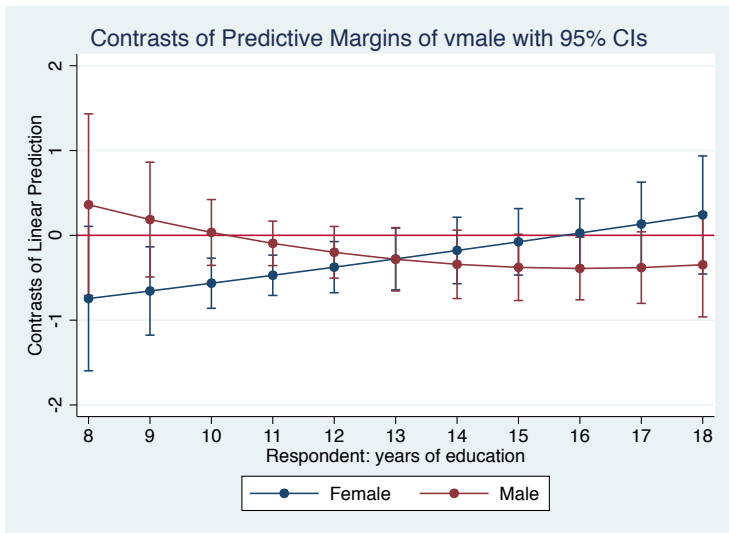
- We see that, after an initial increase, the effect of the vignette sex diminishes (i.e. gets closer to zero) as education increases.
- Still we are looking only at a two-way interaction (vignette sex by education). To explore the full three-way interaction specified in the model we have to go one step further.
- For example, to see how the effect of vignette sex depends on education by sex of respondent, we could type

```
. margins r.vmale, over(rmale) at(reducyrs=(8(1)18))  
. marginsplot, yline(0)
```

or

```
. margins, dydx(vmale) over(rmale) at(reducyrs=(8(1)18))  
. marginsplot, yline(0)
```

Answers: How does the effect of vignette sex depend on respondent's education and sex?



Answers: How does the effect of vignette sex depend on respondent's education and sex?

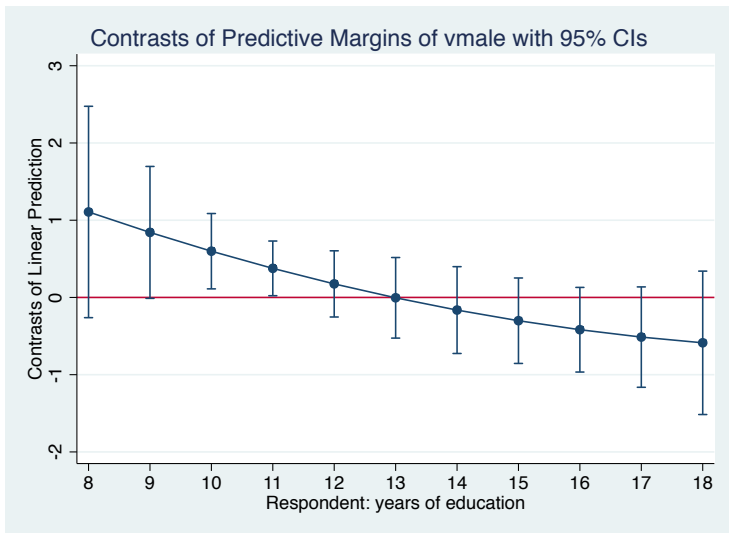
- The pattern of the effect of the vignette sex appears to be somewhat different for female respondents and male respondents.
- To better see how the difference in the effect of the vignette sex between female and male respondents changes with education, we could type

```
. margins r.vmale, over(r.rmale) at(reducyrs=(8(1)18))  
. marginsplot, yline(0)
```

or

```
. margins, dydx(vmale) over(r.rmale) at(reducyrs=(8(1)18))  
. marginsplot, yline(0)
```

Answers: How does the effect of vignette sex depend on respondent's education and sex?



Answers: How does the effect of vignette sex depend on respondent's education and sex?

- In this graph, a difference-in-differences estimate is displayed for each educational level. We see that the difference in effects between female and male respondents is first positive, but then declines and becomes negative after 13 years of education

Answers: Shape of the effect of education

- Up to now, we looked at how the effect of the vignette sex changes depending on education. However, we might also be interested in the main effect of education on the responses.
- To see how the response level changes with education we can simply type

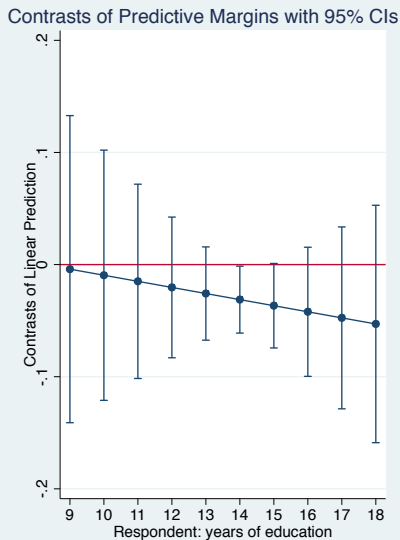
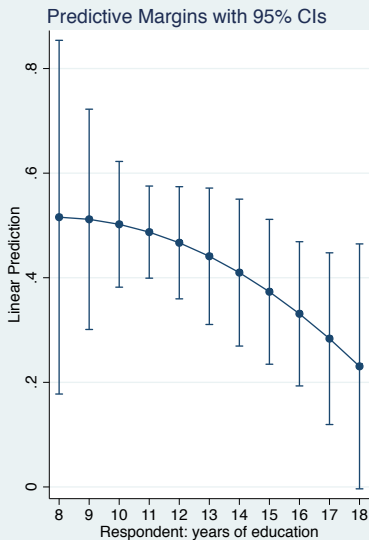
```
. margins, at(reducyrs=(8(1)18))  
. marginsplot
```

- Furthermore, for a picture of how the effect of education changes with educational level, type

```
. margins, at(reducyrs=(8(1)18)) contrast(atcontrast(ar._at))  
. marginsplot, yline(0)
```

The `contrast(atcontrast(ar._at))` option causes `margins` to compute contrasts between predictive margins across adjacent educational levels.

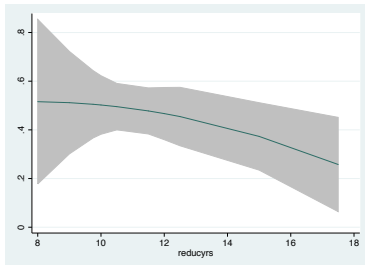
Answers: Shape of the effect of education



Answers: Shape of the effect of education

- Respondents with lower educational level are more likely to judge the income in the vignette as too high than respondents with higher educational level. Furthermore, the (negative) effect of education is getting steeper with additional education.
- A variant of the plot on the left can also be quickly produced by Patrick Royston's `marginscontplot`:

```
. marginscontplot reducyr, ci
```

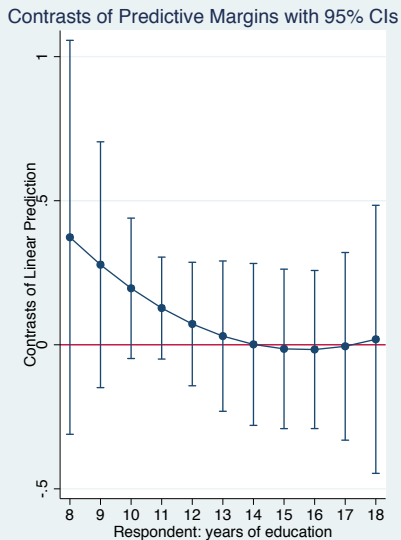
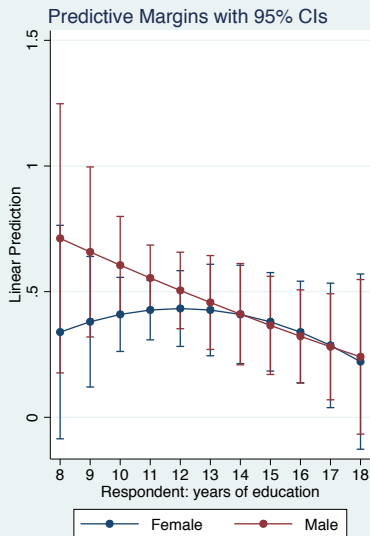


Answers: Shape of the effect of education

- To compare the shape of the effect of education between female and male respondents, we could type something like

```
. margins, at(reducyrs=(8(1)18)) over(rmale)
. marginsplot, name(a, replace)
. margins, at(reducyrs=(8(1)18)) over(r.rmale)
. marginsplot, yline(0) nodraw name(b, replace)
. graph combine a b
```

Answers: Shape of the effect of education



Answers: Shape of the effect of education

- In the left plot, the predictive margins by educational level are shown for female respondents and male respondents.
- In the right plot, the difference between the two curves is plotted. This shows how the effect of the sex of the respondent changes with educational level.

Answers: Can we express the effects in CHF?

- As we can see in the regression output on slide 7, the vignette income has an effect of 0.0010069 on the judgement. An increase in income by 1 CHF increases the expected judgement by 0.0010069 points.
- This means, that 1 point on the judgement scale is worth about 993 CHF:

```
. display 1/_b[vinc]  
993.15639
```

- You can use the `expression()` option in `margins` to compute predictive margins and marginal effects with respect to a rescaled outcome so that, in our case, all effects are expressed in CHF.
- `margins` will take care of the details and also provide consistent standard errors.

Answers: Can we express the effects in CHF?

- Example: Effects of vignette factors

```
. margins, dydx(vmale vmarried veffort) expression(xb()/-_b[vinc])
Average marginal effects          Number of obs   =       1482
Model VCE      : OLS
Expression     : xb()/-_b[vinc]
dy/dx w.r.t.  : 1.vmale 1.vmarried 1.veffort
```

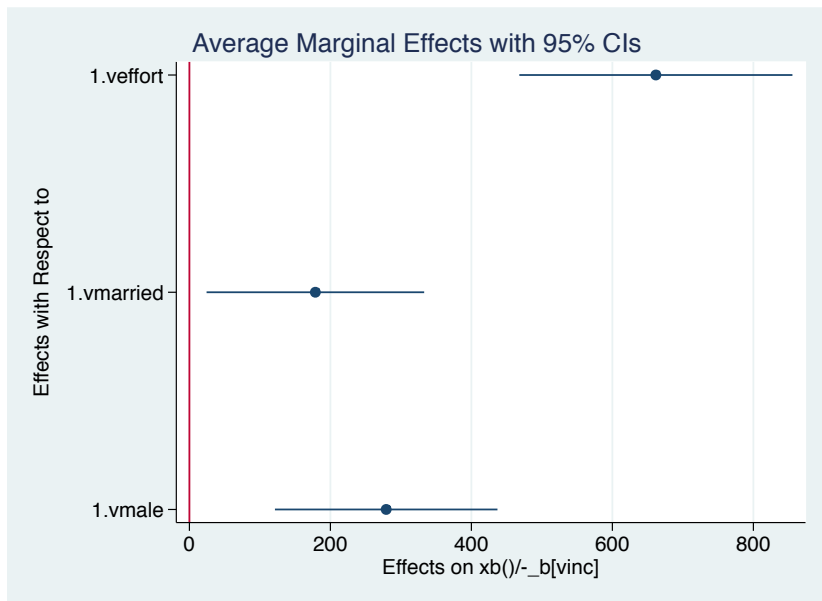
	Delta-method					[95% Conf. Interval]
	dy/dx	Std. Err.	z	P> z		
1.vmale	279.1608	80.52689	3.47	0.001	121.331	436.9906
1.vmarried	178.6802	78.74228	2.27	0.023	24.3482	333.0123
1.veffort	661.7174	98.82199	6.70	0.000	468.0299	855.405

Note: dy/dx for factor levels is the discrete change from the base level.

```
. marginsplot, horizontal recast(scatter) recastci(rspike) ///
>      xline(0) xlabel(, grid) ylabel(, nogrid)
Variables that uniquely identify margins: _deriv
```

- Interpretation: Males “should” get 279 CHF more per month than females, the married should get 179 CHF more, the hard-working should get 661 CHF more.

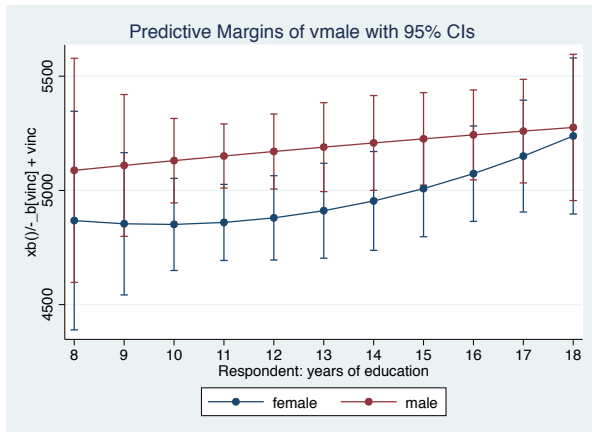
Answers: Can we express the effects in CHF?



Answers: Can we express the effects in CHF?

- Example: “Just” income levels for females and males by education of respondent

```
. margins vmale, at(reducyrs = (8(1)18)) expression(xb()/-_b[vinc] + vinc)
. marginsplot
```



Answers: Interpretation of a logit model

- What is the conditional probability of “too low” depending on different levels of the factor variables?

```
. quietly logit toolow vinc i.vmale i.vmarried i.veffort  
. margins vmale vmarried veffort
```

```
Predictive margins                                Number of obs   =       1482  
Model VCE      : OIM  
Expression     : Pr(toolow), predict()
```

	Margin	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
vmale						
0	.1652877	.012963	12.75	0.000	.1398807	.1906946
1	.2215201	.0145671	15.21	0.000	.192969	.2500711
vmarried						
0	.1725705	.0133054	12.97	0.000	.1464925	.1986485
1	.2131927	.0142477	14.96	0.000	.1852677	.2411177
veffort						
0	.1115456	.0113453	9.83	0.000	.0893093	.1337819
1	.2749636	.015868	17.33	0.000	.2438629	.3060642

Answers: Interpretation of a logit model

- What is the (average) marginal effect of the vignette factors on the probability of “too low”?

```
. margins, dydx(vmale vmarried veffort)
Average marginal effects           Number of obs   =           1482
Model VCE       : OIM
Expression      : Pr(toolow), predict()
dy/dx w.r.t.    : 1.vmale 1.vmarried 1.veffort
```

	Delta-method		z	P> z	[95% Conf. Interval]	
	dy/dx	Std. Err.				
1.vmale	.0562324	.0195033	2.88	0.004	.0180066	.0944582
1.vmarried	.0406222	.0194988	2.08	0.037	.0024053	.0788392
1.veffort	.1634179	.0195074	8.38	0.000	.1251842	.2016517

Note: dy/dx for factor levels is the discrete change from the base level.

- We see that, for example, the average marginal effect of the vignette sex is 5 percentage points. That is, everything else equal, we would expect a 5 percentage point increase in the proportion of respondents who judge the vignette income as too low if we change the vignette sex from female to male.

What margins and marginsplot can't do

- The default for continuous variables is to compute marginal effects as first derivatives. Discrete change effects for continuous variables can only be computed for special cases (e.g. min to max, in steps across the scale).
 - ▶ It would be nice to be able to compute discrete change effects around observed values (e.g. +/- half a standard deviation).
- Marginal effects for transformed covariates can only be computed in special cases (e.g. quadratic).
- `margins` can only deal with one equation at the time in models with multiple outcomes (e.g. `mlogit`).
- `margins` can be excessively slow on big datasets.
- `marginsplot` can only handle results from `margins` and can only display one set of results at the time.

New command: `regplot`

- A new command called `regplot` provides a solution for the last problem.

`regplot models, options`

- `regplot` uses `marginplot` internally, but it can be applied to any estimation results, be it by `margin` or not.
- Multiple estimation results can be combined in a single graph.
- By default, `regplot` creates a horizontal “dot plot” of the coefficients found in `e(b)` and includes spikes for confidence intervals. I call this a “regression plot”. Others sometimes call it an “airplane plot”.

New command: regplot

- How to specify *models*:

- ▶ Models in separate plots:

`(modelname, options) || (modelname, options) ...`

- ▶ Several models in one plot:

`(modelname, options) (modelname, options) ...`

This command has been published as `coefplot`.

- ▶ Append models:

`(modelname, options \ modelname, options) ...`

- ▶ A combination of the above.

Plot of raw coefficients

- regplot can be applied directly after an estimation command to produce a plot of the estimated coefficients.

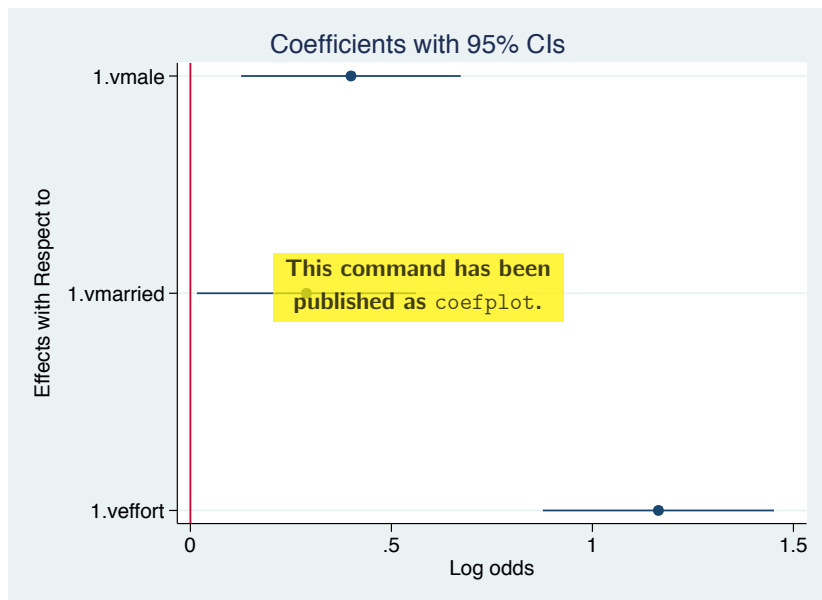
```
. logit toolow vinc i.vmale i.vmarried i.veffort, nolog
```

```
Logistic regression                Number of obs   =       1482
                                   LR chi2(4)         =       140.79
                                   Prob > chi2        =       0.0000
Log likelihood = -656.55323        Pseudo R2      =       0.0968
```

toolow	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
vinc	-.0013663	.0001789	-7.64	0.000	-.0017169	-.0010157
1.vmale	.3994001	.1393606	2.87	0.004	.1262584	.6725417
1.vmarried	.2886296	.1389959	2.08	0.038	.0162027	.5610565
1.veffort	1.164184	.1466717	7.94	0.000	.8767125	1.451655
_cons	4.939563	.9606374	5.14	0.000	3.056748	6.822378

```
. regplot ., keep(1.*) xline(0) xtitle(Log odds)
```

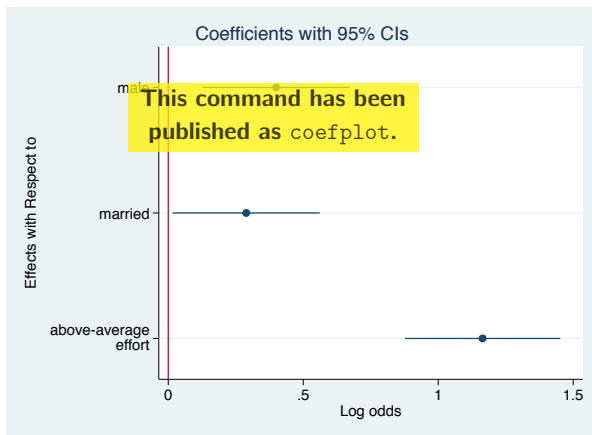
Plot of raw coefficients



Label the coefficients

- Coefficients are positioned on the y-axis at 1, 2, 3, ... (from top). Hence, you can use `ylabel()` to define custom labels.

```
. regplot ., keep(1.*) xline(0) xtitle(Log odds) ///  
>   ylabel(1 "male" 2 "married" 3 `"'above-average" "effort"'`) ///  
>   yscale(range(0.75 3.25))
```



Plot results from margins

- regplot can also be applied after margins, if the post option is specified with margins:

```
. margins, dydx(vmale vmarried veffort) post
```

```
Average marginal effects          Number of obs   =          1482
```

```
Model VCE      : OIM
```

```
Expression    : Pr(toolow)
```

```
dy/dx w.r.t. : 1.vmale 1.vmarried 1.veffort
```

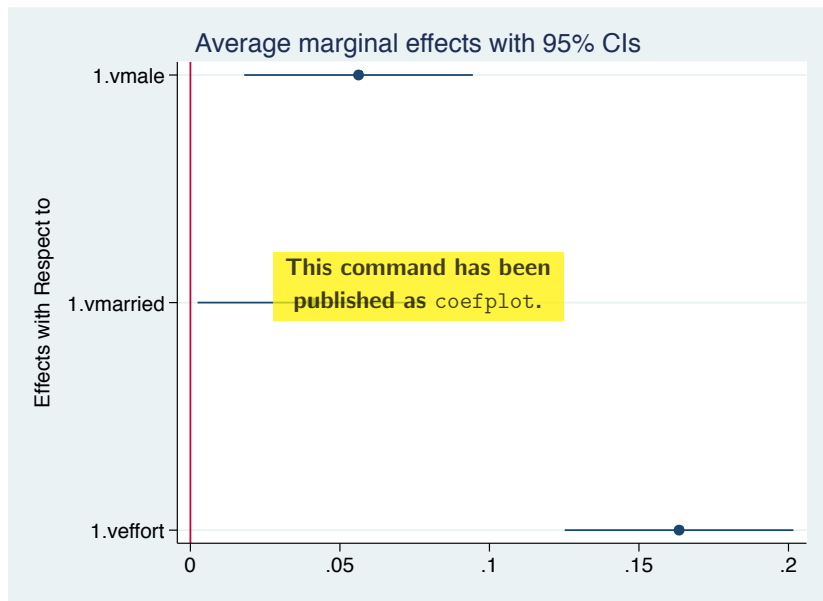
This command has been published as `coefplot`.

	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.vmale	.0562324	.0195033	2.88	0.004	.0180066	.0944582
1.vmarried	.0406222	.0194988	2.08	0.037	.0024053	.0788392
1.veffort	.1634179	.0195074	8.38	0.000	.1251842	.2016517

Note: dy/dx for factor levels is the discrete change from the base level.

```
. regplot ., xline(0) keep(1.*) title(Average marginal effects with 95% CIs)
```

Plot results from margins



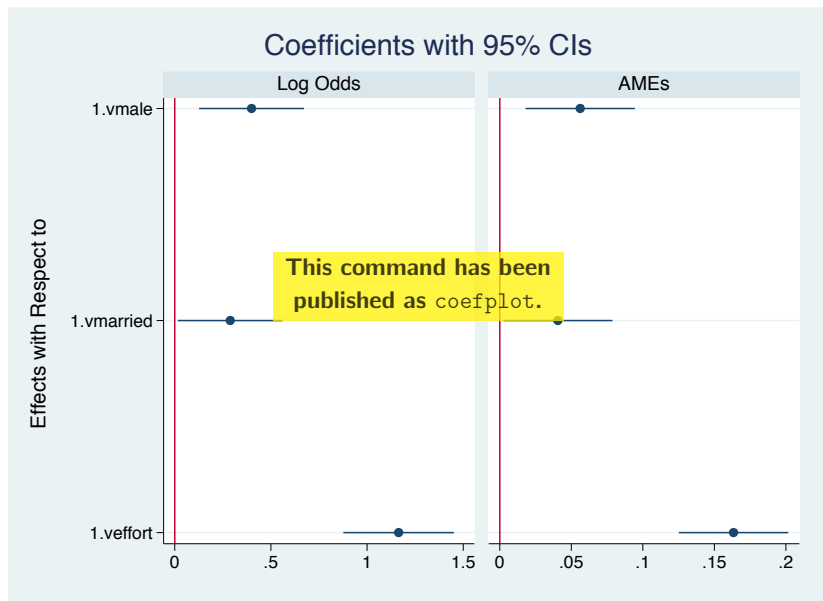
Combine raw coefficients and AMEs

- `regplot` can be applied to stored models. For example, we could combine raw coefficients from `logit` and corresponding average marginal effects from `margins`

```
. quietly logit toolow v1nc 1.vmale 1.vmarried 1.veffort  
. estimates store raw  
. quietly margins, dydx(vmale vmarried veffort) post  
. estimates store ame  
. regplot (raw, bylabel(Log Odds)) || (ame, bylabel(AMEs)) ///  
> , xline(0) keep(1.*) byopts(xrescale)
```

This command has been published as `coefplot`.

Combine raw coefficients and AMEs

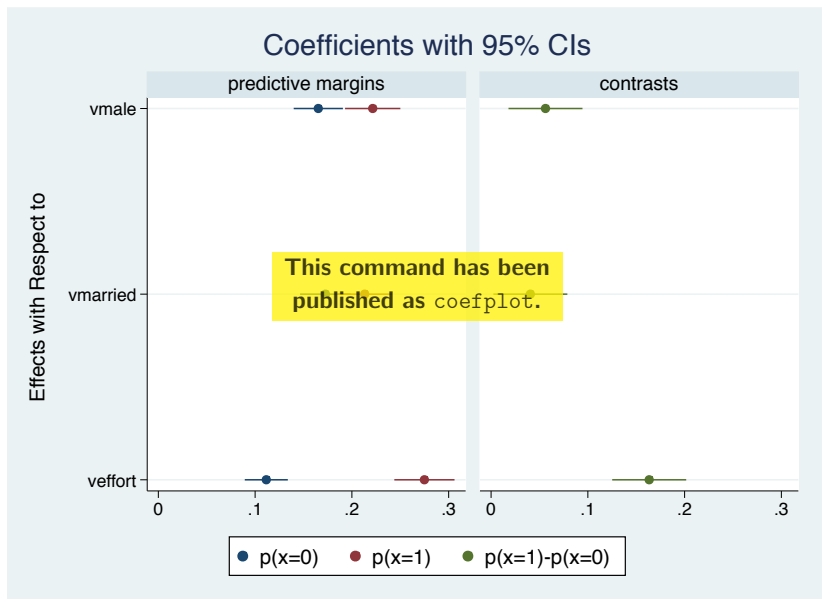


Combine predictive margins and contrasts

- We could also predictive margins and contrasts/marginal effects in one graph.

```
. quietly logit toolow vinc i.vmale i.vmarried i.veffort
. estimates store raw
. quietly margins vmale vmarried veffort, post
. estimates store margins This command has been
. estimates restore raw published as coefplot.
(results raw are active now)
. quietly margins, dydx(vmale vmarried veffort) post
. estimates store contrasts
. regplot (margins, rename(0bn. "") drop(1.*) label(p(x=0))) ///
> (margins, rename(1. "") drop(0bn.*) label(p(x=1)) ///
> bylabel(predictive margins)) || ///
> (contrasts, rename(1. "") drop(0.*) label(p(x=1)-p(x=0)) ///
> bylabel(contrasts)) , norecycle legend(rows(1))
```


Combine predictive margins and contrasts



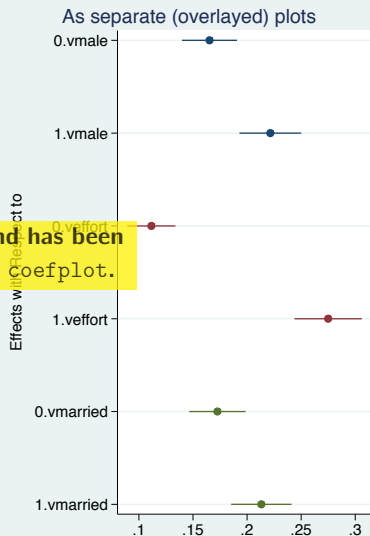
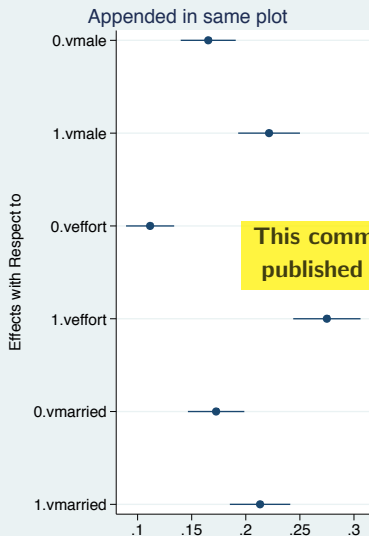
Append models

- Use \ to append models in one plot.

```
. quietly logit toolow vinc i.vmale i.vmarried i.veffort
. estimates store logit
. quietly margins vmale, post
. estimates store vmale
. estimates restore logit
(results logit are active now)
. quietly margins vmarried, post
. estimates store vmarried
. estimates restore logit
(results logit are active now)
. quietly margins veffort, post
. estimates store veffort
. regplot (vmale \ veffort \ vmarried), title(Appended in same plot) ///
> nodraw name(a, replace)
. regplot (vmale) (veffort) (vmarried), title(As separate (overlaid) plots) ///
> legend(off) nodraw name(b, replace)
. graph combine a b
```

This command has been published as coefplot.

Append models



This command has been published as `coefplot`.

Plot coefficients from mlogit

- In multiequation models, use the eq() option to select the equation to be plotted.

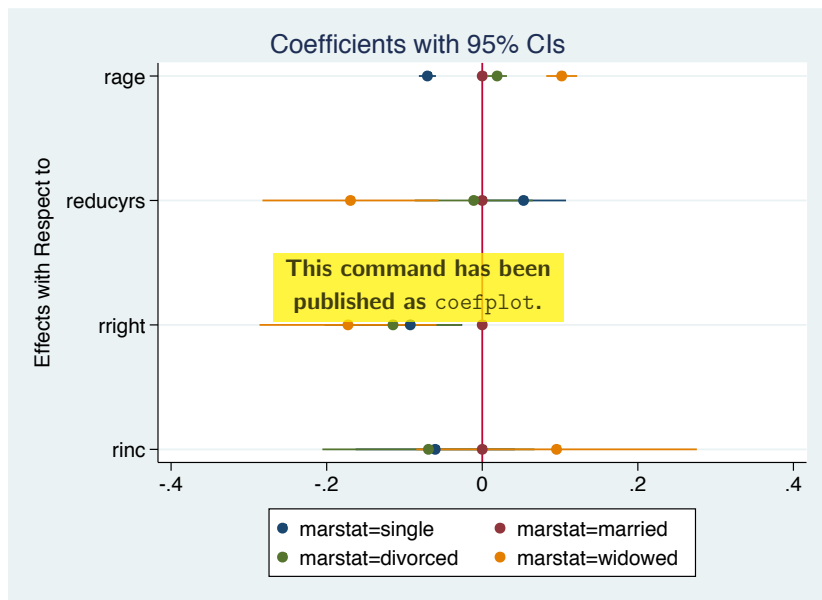
```
. mlogit rmarstat rage reducyrs rright rinc, nolog
Multinomial logistic regression      Number of obs   =      1482
                                      LR chi2(12)     =      477.71
                                      Prob > chi2     =      0.0000
Log likelihood = -1380.6739          Pseudo R2      =      0.1475
```

rmarstat	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
single						
rage	-.0705039	.0055962	-12.60	0.000	-.0814724	-.0595355
reducyrs	.0531021	.0278531	1.91	0.057	-.0014889	.1076931
rright	-.0924911	.0340842	-2.71	0.007	-.1592849	-.0256973
rinc	-.0604214	.0522317	-1.16	0.247	-.1691334	.0482903
_cons	2.533033	.4611503	5.49	0.000	1.629195	3.436871
married	(base outcome)					
divorced						
rage	.0190981	.0064624	2.96	0.003	.006432	.0317642
reducyrs	-.0109678	.0386512	-0.28	0.777	-.0867228	.0647873
rright	-.1147781	.0449214	-2.56	0.011	-.2028225	-.0267338
rinc	-.0691778	.0695684	-0.99	0.320	-.2055293	.0671736
_cons	-1.927327	.633678	-3.04	0.002	-3.169313	-.6853408
widowed						
rage	.1021225	.0101098	10.10	0.000	.0823077	.1219373
reducyrs	-.1693922	.0577359	-2.93	0.003	-.2825526	-.0562319
rright	-.1726326	.0580334	-2.97	0.003	-.286376	-.0588892
rinc	.0955222	.0920018	1.04	0.299	-.084798	.2758423
_cons	-6.098965	.9666954	-6.31	0.000	-7.993653	-4.204277

```
. estimates store marstat
. regplot (marstat, eq(single)) ///
> (marstat, eq(married)) ///
> (marstat, eq(divorced)) ///
> (marstat, eq(widowed)), nocons xline(0)
```

This command has been published as coefplot.

Plot coefficients from mlogit



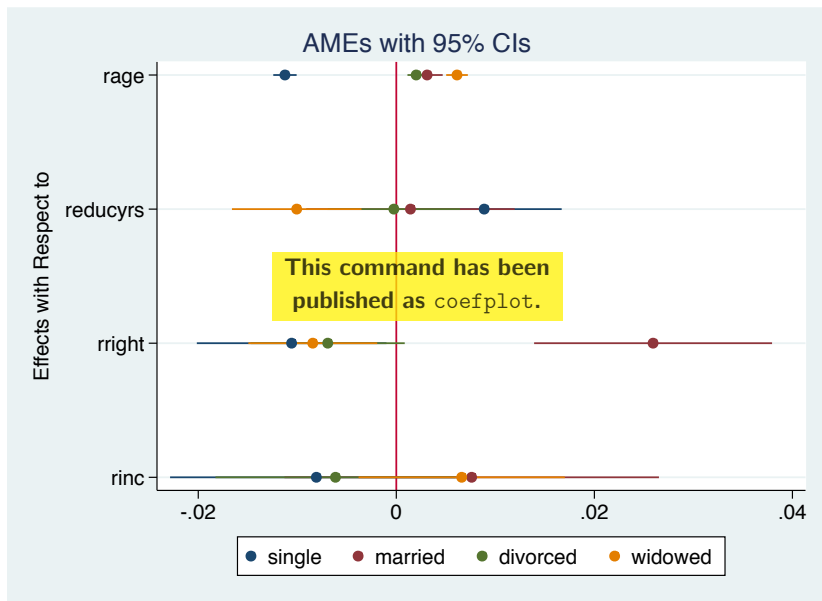
Plot marginal effects from mlogit

- To plot marginal effects for an `mlogit` model you have to run `margins` for each outcome.

```
. quietly margins, dydx(*) predict(outcome(single)) post
. estimates store single
. estimates restore marstat
(results marstat are active now)
. quietly margins, dydx(*) predict(outcome(married)) post
. estimates store married
. estimates restore marstat
(results marstat are active now)
. quietly margins, dydx(*) predict(outcome(divorced)) post
. estimates store divorced
. estimates restore marstat
(results marstat are active now)
. quietly margins, dydx(*) predict(outcome(widowed)) post
. estimates store widowed
. regplot single married divorced widowed, legend(row(1)) xline(0) ///
> title(AMEs with 95% CIs)
```

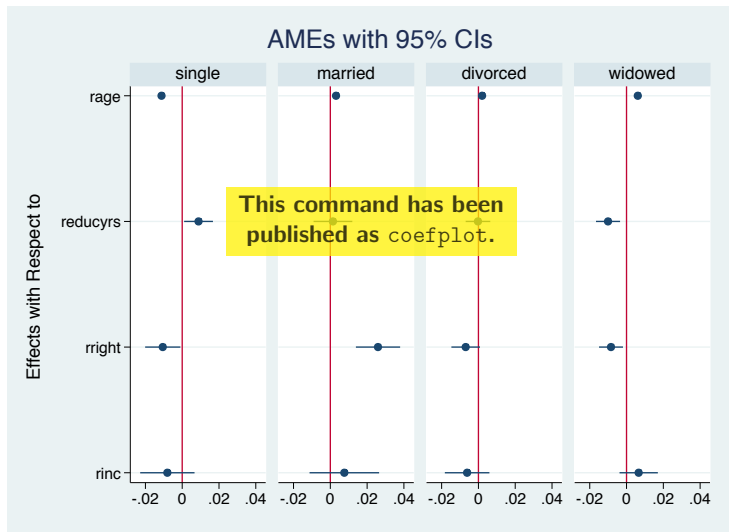
This command has been published as `coefplot`.

Plot marginal effects from mlogit



Plot marginal effects from mlogit

```
. regplot single || married || divorced || widowed, xline(0) ///  
> byplot(rows(1) title(AMEs with 95% CIs))
```



References

- Rising, B. (2012). Working in the margins to plot a clear course. Presentation at the 10th German Stata Users Group Meeting in Berlin.
- Rising, B. (2012). How to get an edge with margins and marginsplot. Presentation at the 2012 UK Stata Users Group Meeting in London.
- Royston, P. (forthcoming). marginscontplot: plotting the marginal effects of continuous predictors. *The Stata Journal*.
- Williams, R. (2012). Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal* 12(2):308–331.