LAB 3: Complex Context-Conditionality: Nonlinear Interaction Models

```
use "…\MultipleHandsOnWheel.dta", clear
```

Estimate the MHoW Model by NLS:

$$
\begin{aligned}
E(\pi) = \beta_0 + \beta_{l1}\pi_{t-1} + \beta_{l2}\pi_{t-2} + \beta_e E \times \beta_{\pi*}\pi_a + \left(1 - \beta_e E\right) \\
\times \begin{cases} \left[\begin{array}{l} \left(\beta_{gp}GP + \beta_{ey}EY + \beta_{up}UP + \beta_{bc}BC + \beta_{aw}AW + \beta_{fs}FS + \beta_{te}TE + \beta_a \pi_a\right) \\ \times\left(1 - \beta_{c1}C\right) + \beta_{c1}C \cdot \beta_{c2} \end{array} \right] \\ \times(1 - \beta_{sp}SP - \beta_{mp}MP) + \beta_{sp}SP \times \beta_{\pi*}\pi_{sp} + \beta_{mp}MP \times \beta_{\pi*}\pi_{mp} \end{cases}
\end{aligned}
$$

help nl

```
nl (inf=(((1-
{b_c1}*cbi)*({b_gp}*gp+{b_ey}*ey1+{b_up}*up+{b_bc}*bc+{b_aw}*aw+{b_fs}*fs+{b_soe}
*soe+{b_infa}*infa)+{b_c1}*cbi*{b_c2})*(1-{b_sp}*speg-
{b_mp}*gpeg)+{b_sp}*speg*{b_pia}*spinf+{b_mp}*gpeg*{b_pia}*gpinf)*(1-
{b_ckao}*ckao)+{b_ckao}*ckao*{b_pia}*infa+{rho1}*inf1+{rho2}*inf2+{intcpt}) if
sample==1
```

TIP: Even if working interactively, as we are here, you may wish to type the estimation equation in an editor that keeps track of parentheses (to help avoid unmatched parentheses or braces & other typo’s) & copy into Stata.

$$
E(\pi) \approx \left\langle \begin{array}{l}
.53^{.30} + .55^{.05}\pi_{t-1} - .12^{.04}\pi_{t-2} + .44^{.14}E \cdot .59^{.07} \cdot \pi_a + \\
\left(1 - .44^{.14}E\right) \cdot \left\{ \begin{array}{l}
1.0^{.05}SP \cdot .59^{.07}\pi_{sp} + .22^{.12}MP \cdot .59^{.07}\pi_{mp} + \\
\left(1 - 1.0^{.05}SP - .22^{.12}MP\right) \cdot \left[\begin{array}{l}
1.0^{.11}C \cdot \left(-.59^{1.2}\right) + \\
\left(1 - 1.0^{.11}C\right) \cdot \left(\begin{array}{l}
-.60^{.30}GP + 2.6^{1.3}EY + 16^{4.6}UP - 11^{2.4}BC \\
+1.2^{.49}AW - 1.1^{.30}FS - 8.2^{4.9}TE + .64^{.24}\pi_a
\end{array} \right)
\end{array} \right]
\end{array} \right\}
\end{array} \right\rangle
$$

inf	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b_c1	1.034707	.1052662	9.83	0.000	.8279996	1.241414
/b_gp	-.5968402	.2182052	-2.74	0.006	-1.025321	-.1683592
/b_ey	2.597585	1.048071	2.48	0.013	.53953	4.65564
/b_up	16.21009	3.597138	4.51	0.000	9.146529	23.27364
/b_bc	-10.67542	1.749681	-6.10	0.000	-14.1112	-7.23964
/b_aw	1.181586	.3281272	3.60	0.000	.5372558	1.825916
/b_fs	-1.093103	.2243905	-4.87	0.000	-1.53373	-.6524763
/b_soe	-8.235813	4.029253	-2.04	0.041	-16.1479	-.3237282
/b_infa	.6370324	.1653597	3.85	0.000	.3123221	.9617427
/b_c2	-.5943391	1.189165	-0.50	0.617	-2.929455	1.740777
/b_sp	1.036251	.0634138	16.34	0.000	.9117281	1.160775
/b_mp	.2169103	.0976532	2.22	0.027	.0251527	.4086679
/b_pia	.5938107	.0646409	9.19	0.000	.466878	.7207434
/b_ckao	.4427236	.1133632	3.91	0.000	.2201167	.6653305
/rho1	.548679	.0382853	14.33	0.000	.4734998	.6238583
/rho2	-.1206175	.0358316	-3.37	0.001	-.1909786	-.0502564
/intcpt	.5330137	.3030496	1.76	0.079	-.0620729	1.1281

Note: Std.errs. reported in the paper are from Newey-West HAC consistent s.e.'s, so these estimates not as close to the published results on those. Even more sensible than Newey-West for these data—though was good reason to use those here too—would be estimates of the variance-covariance of the estimated coefficients that are consistent to clustering:

Repeat with V(b) clustered by country:

```
. nl ([…]) if sample==1 , vce(cluster ctry)
```

(Std. Err. adjusted for 21 clusters in ctry)

inf	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b_c1	1.034707	.1204492	8.59	0.000	.7834541	1.285959
/b_gp	-.5968402	.2433577	-2.45	0.023	-1.104475	-.089205
/b_ey	2.597585	1.464517	1.77	0.091	-.4573432	5.652513
/b_up	16.21009	5.951881	2.72	0.013	3.794679	28.62549
/b_bc	-10.67542	2.989398	-3.57	0.002	-16.91119	-4.439645
/b_aw	1.181586	.6140924	1.92	0.069	-.0993882	2.46256
/b_fs	-1.093103	.3945214	-2.77	0.012	-1.91606	-.2701459
/b_soe	-8.235813	5.214604	-1.58	0.130	-19.11329	2.64166
/b_infa	.6370324	.2630528	2.42	0.025	.0883139	1.185751
/b_c2	-.5943391	1.243691	-0.48	0.638	-3.188634	1.999955
/b_sp	1.036251	.035687	29.04	0.000	.9618096	1.110693
/b_mp	.2169103	.1334497	1.63	0.120	-.0614608	.4952814
/b_pia	.5938107	.0625182	9.50	0.000	.4634	.7242214
/b_ckao	.4427236	.1450815	3.05	0.006	.140089	.7453583
/rho1	.548679	.0554601	9.89	0.000	.4329914	.6643667
/rho2	-.1206175	.0260939	-4.62	0.000	-.1750484	-.0661866
/intcpt	.5330137	.2902339	1.84	0.081	-.0724037	1.138431

Calculate estimated electoral-cycle impulse-magnitudes over actual sample country-years:

. Help nl postestimation [then click on **predictnl**]

$$E\left(\frac{d\pi}{dC}\right)=\begin{cases}(1-b_{e}E)\times(1-b_{sp}SP-b_{mp}.22MP)\times\\ \left(b_{c_1}b_{c_2}-b_{c_1}\left[b_{gp}GP+b_{ey}EY+b_{up}UP+b_{bc}BC+b_{aw}AW+b_{fs}FS+b_{te}TE+b_{\pi_a}.64\pi_{a})\right]\right)\end{cases}$$

Note: **nl** can also estimate models giving any linear-additive sub-components as **{xb: *varlist*}**. Let's re-estimate the previous model that way:

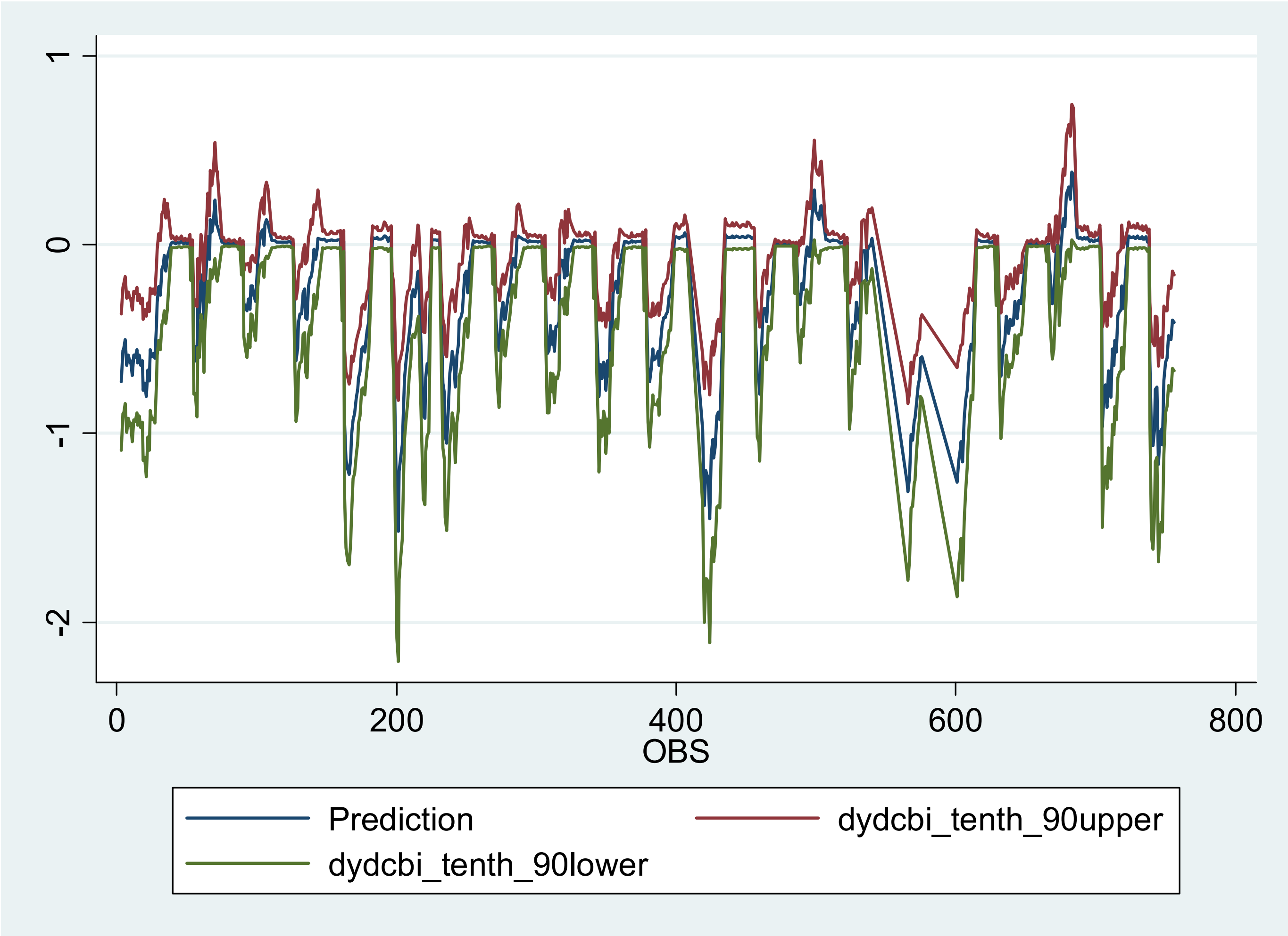
```
nl (inf=(((1-{b_c1}*cbi)*({xb:gp ey1 up bc aw fs soe
infa})+{b_c1}*cbi*{b_c2})*(1-{b_sp}*speg-
{b_mp}*gpeg)+{b_sp}*speg*{b_pia}*spinf+{b_mp}*gpeg*{b_pia}*gpinf)*(1-
{b_ckao}*ckao)+{b_ckao}*ckao*{b_pia}*infa+{rho1}*inf1+{rho2}*inf2+{intcpt}) if
sample==1 , vce(cluster ctry)
```

Even if you do it this way, however, do not add **xb()** to the subsequent **predictnl** thinking it will include only that **xb** part. **xb()** is stata syntax for the entire link function. So, now we need to write the **predictnl** this way:

```
. predictnl dydcbi_tenth=.1*(1-_b[/b_ckao]*ckao)*(1-_b[/b_sp]*speg-
_b[/b_mp]*gpeg)*(_b[/b_c1]*_b[/b_c2]-
_b[/b_c1]*(_b[/xb_gp]*gp+_b[/xb_ey1]*ey1+_b[/xb_up]*up+_b[/xb_bc]*bc+_b[/xb_aw]*a
w+_b[/xb_fs]*fs+_b[/xb_soe]*soe+_b[/xb_infa]*infa)) if sample==1 ,
se(se_dydcbi_tenth)
```

Plot estimated electoral-cycle impulse-magnitudes with confidence intervals:

```
. Help graph
. gen dydcbi_tenth_90upper=dydcbi_tenth+1.645*se_dydcbi_tenth
(96 missing values generated)
. gen dydcbi_tenth_90lower=dydcbi_tenth-1.645*se_dydcbi_tenth
(96 missing values generated)
. graph twoway line dydcbi_tenth dydcbi_tenth_90upper dydcbi_tenth_90lower obs
```



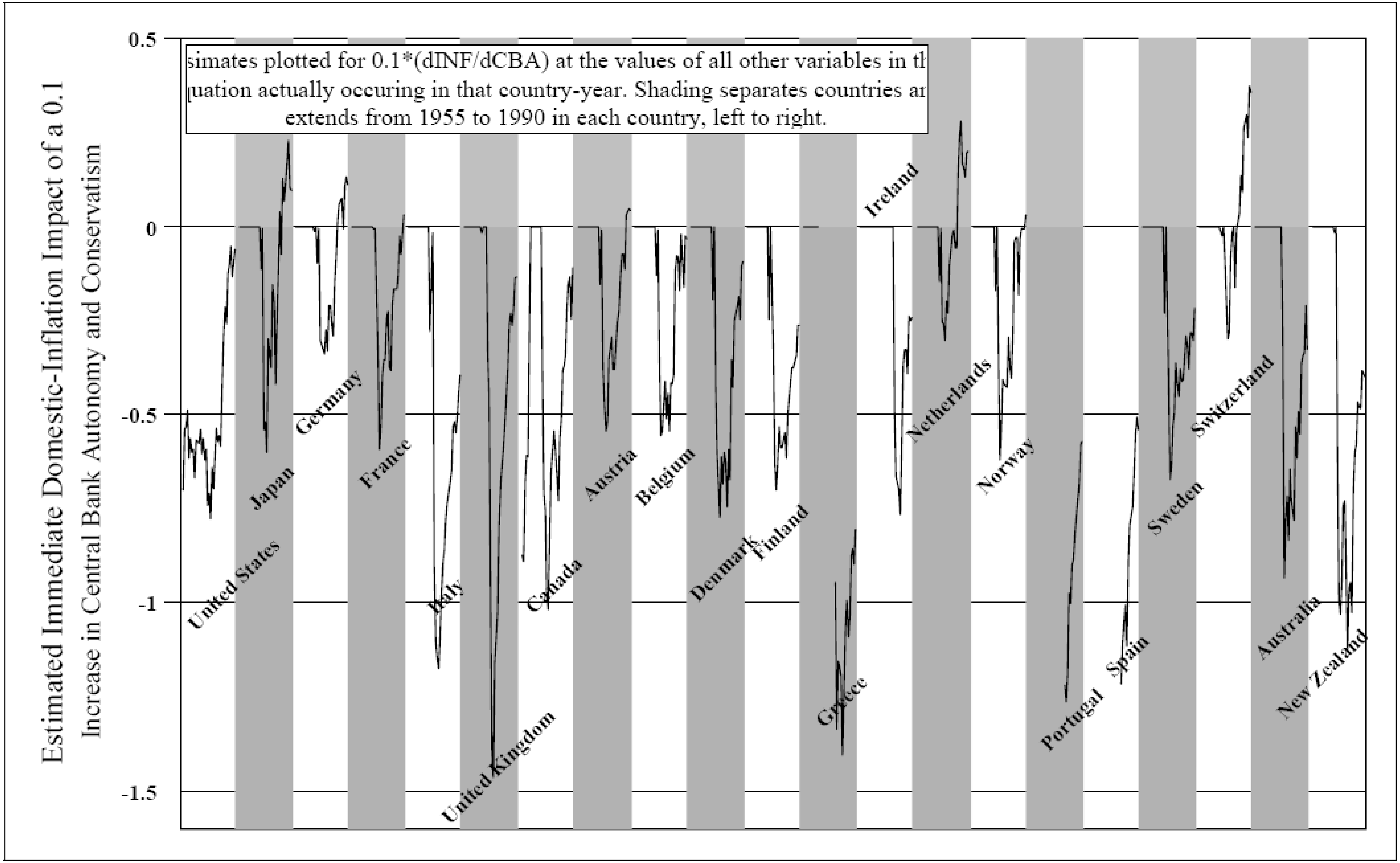


Figure 4: Estimated First-Year Domestic-Inflation Impact of 0.1 Increase in CBA in 21 Countries, 1957-90

Point estimates, Wald tests, & confidence intervals for nonlinear functions of coefficients:

```
. help nlcom
. nlcom _b[/b_c1]*_b[/b_c2]
```

[Estimated inflation-target times CBI=1…]

```
       _nl_1:  _b[/b_c1]*_b[/b_c2]
------------------------------------------------------------------------------
         inf |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -.6149666   1.279853    -0.48   0.636    -3.284693     2.05476
```

Could use this to generate tables like:

		E=0.40			*E=0.65*			*E=0.90*		
		SP=MP=0	*MP=1*	*SP=1*	*SP=MP=0*	*MP=1*	*SP=1*	*SP=MP=0*	*MP=1*	*SP=1*
		Estimated Impact of 1-Unit Rightward Shift in Government Partisanship ($d\pi/dGP$)								
	0.26	$-0.359^{.17}$	$-0.281^{.15}$	$-0.000^{.02}$	$-0.311^{.15}$	$-0.243^{.13}$	$-0.000^{.02}$	$-0.262^{.12}$	$-0.206^{.11}$	$-0.000^{.01}$
CBA =	***0.46***	$-0.257^{.12}$	$-0.202^{.10}$	$-0.000^{.01}$	$-0.223^{.10}$	$-0.174^{.09}$	$-0.000^{.01}$	$-0.188^{.09}$	$-0.147^{.08}$	$-0.000^{.01}$
	0.66	$-0.156^{.07}$	$-0.122^{.06}$	$-0.000^{.01}$	$-0.135^{.06}$	$-0.106^{.05}$	$-0.000^{.01}$	$-0.114^{.05}$	$-0.089^{.05}$	$-0.000^{.01}$
		Estimated Impact of a Post-Election Year ($d\pi/dEY$)								
	0.26	$+1.563^{.79}$	$+1.224^{.61}$	$+0.000^{.09}$	$+1.352^{.69}$	$+1.059^{.53}$	$+0.000^{.07}$	$+1.142^{.60}$	$+0.894^{.47}$	$+0.000^{.06}$
CBA=	***0.46***	$+1.120^{.57}$	$+0.877^{.44}$	$+0.000^{.06}$	$+0.970^{.50}$	$+0.759^{.39}$	$+0.000^{.05}$	$+0.819^{.44}$	$+0.641^{.34}$	$+0.000^{.05}$
	0.66	$+0.678^{.37}$	$+0.531^{.29}$	$+0.000^{.04}$	$+0.587^{.32}$	$+0.459^{.25}$	$+0.000^{.03}$	$+0.495^{.28}$	$+0.388^{.22}$	$+0.000^{.03}$
		Estimated Impact of 10% Increase in Union Density ($0.1 \cdot d\pi/dUP$)								
	0.26	$+0.98^{.25}$	$+0.76^{.18}$	$+0.00^{.05}$	$+0.84^{.21}$	$+0.66^{.16}$	$+0.00^{.04}$	$+0.71^{.19}$	$+0.56^{.14}$	$+0.00^{.04}$
CBA=	***0.46***	$+0.70^{.18}$	$+0.55^{.13}$	$+0.00^{.04}$	$+0.61^{.15}$	$+0.47^{.11}$	$+0.00^{.03}$	$+0.51^{.14}$	$+0.40^{.10}$	$+0.00^{.03}$
	0.66	$+0.42^{.13}$	$+0.33^{.10}$	$+0.00^{.02}$	$+0.37^{.11}$	$+0.29^{.08}$	$+0.00^{.02}$	$+0.31^{.10}$	$+0.24^{.08}$	$+0.00^{.02}$

Estimated election-year impulse under low CBI, basket peg, and low small-financial-openness:

```
. nlcom (1-_b[/b_c1]*.26)*(1-_b[/b_mp])*(1-_b[/b_ckao]*.4)*_b[/xb_ey1]
       _nl_1:  (1-_b[/b_c1]*.26)*(1-_b[/b_mp])*(1-_b[/b_ckao]*.4)*_b[/xb_ey1]
------------------------------------------------------------------------------
         inf |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   1.223594   .6840747     1.79   0.089    -.2033612    2.650549
```

Working with *QualDep* Models:

Probit Models with Linear-Additive Argument:

```
use "…\ext_det.dta" , clear

tabstat det_suc imbalfor stbalfor ltbalfor nuke alliance arms_xfr for_trde fbf
tft putdn stale pdip_def pdet_suc capit arm_spt, statistics( mean max min p25 p50
p75 sd kurtosis ) columns(variables)

probit det_suc imbalfor for_trde nuke

help mfx
mfx
```

`help nlcom` **Estimated effects of defender nuclear-capacity on probability deterrence success:**

```
nlcom normal(_b[imbalfor]*1.209+_b[for_trde]*1.744828+_b[nuke]+_b[_cons])-
normal(_b[imbalfor]*1.209+_b[for_trde]*1.744828+_b[_cons])
```

`help plotfds` **[install if necessary]**

```
net from http://gking.harvard.edu/clarify/
net install clarify
net get clarify

estsimp probit det_suc imbalfor for_trde nuke
plotfds, discrete(nuke) continuous(imbalfor for_trde)
```

Probit Models with Linear-Interactive Argument:

```
gen trade_imbalfor=for_trde*imbalfor

probit det_suc imbalfor for_trde trade_imbalfor nuke

help inteff     [install if necessary]
inteff det_suc imbalfor for_trde trade_imbalfor
```

Note that `inteff` **is only written to apply Ai & Norton's formula for the cross-derivative or cross-difference to the actual values of the variables in your dataset. It also does not calculate first differences (effects) for you, but rather cross-derivatives or -differences (effects on effects) only.** `Predictnl` **also applies to your actual variable values. You could get interactive first-differences effects for specific values from** `nlcom`**:**

```
nlcom normal(_b[imbalfor]*1.209+_b[for_trde]*2+_b[trade_imbalfor]*2.418+_b[nuke]+_b[_cons])-
normal(_b[imbalfor]*1.209+_b[for_trde]*1+_b[trade_imbalfor]*1.209+_b[nuke]+_b[_cons])
```

You could write a loop or generate a vector of values yourself for `imbalfor` **&/or** `for_trade` **to do either of these reasonably quickly for a whole range of values, and plot the results. You could also do it using Matt Golder's code, at http://homepages.nyu.edu/~mrg217/interaction.html#code or using *Clarify*, already installed above.]**

```
help estsimp
help setx
help simqi
```

To use the bootstrap simulation techniques that *Clarify* automated, you would have to write a loop to recalculate your difference or marginal for each of a sequence of conditioning-variable(s) values.

Ordered Probit Models with Linear-Additive Argument:

```
use "C:\Work\WPDOCS\Syllabi\Essex - Specification\Labs\winlose.dta", clear
findit indeplist
```
[install if necessary]

[first, let's run Fred's very nice do file:]

```
do "C:\Work\WPDOCS\Syllabi\Essex - Specification\Labs\306hwk04.do"
```

[now, let's conduct our own analysis (n.b., variables differ):]

```
use "C:\Work\WPDOCS\Syllabi\Essex - Specification\Labs\winlose.dta", clear

ologit chalwin3 chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl rlstake3
relres4 chalnuke defnukes

estsimp ologit chalwin3 chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl
rlstake3 relres4 chalnuke defnukes

plotfds , continuous(chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl
rlstake3 relres4) discrete(chalnuke defnukes) outcome(1)

plotfds , continuous(chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl
rlstake3 relres4) discrete(chalnuke defnukes) outcome(2)

plotfds , continuous(chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl
rlstake3 relres4) discrete(chalnuke defnukes) outcome(3)
```

[Notice, though, that `audresq4=(chaldemc-defdemoc)relres4`**:]**

Ordered Probit Models with Linear-Interactive Argument:

```
drop b1 b2 b3 b4 b5 b6 b7 b8 b9 b10 b11 b12
estsimp ologit chalwin3 chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl
rlstake3 relres4 chalnuke defnukes
plotfds , continuous(chaldemc defdemoc audresq4 demcapbl allycpbl relcapbl
rlstake3 relres4) discrete(chalnuke defnukes) outcome(3) label
```

[This means that more meaningful first-differences should account the nonlinearity in X, i.e. the interaction. Let's shorten the model to make matters manageable:]

```
drop b1 b2 b3 b4 b5 b6 b7 b8 b9 b10 b11 b12
estsimp ologit chalwin3 chaldemc defdemoc audresq4 relres4
```

$$\begin{aligned}\text{ChallWin}^* &= b_{cd}\text{ChallDem} + b_{dd}\text{DefDem} + b_{rr}\text{RelRes4} + b_{aa}\text{AudCostAdv} + e\\ &= b_{cd}\text{ChallDem} + b_{dd}\text{DefDem} + b_{rr}\text{RelRes4} + b_{aa}(\text{ChallDem} - \text{DefDem})\text{RelRes4} + e\end{aligned}$$

$$\begin{aligned}\Rightarrow \frac{d\,\Pr(\text{ChallWin}{=}J)}{d\text{ChallDem}} &= \left\{\Phi(\tau_J \middle| \text{ChallWin}^*_{\text{Xmean,ChallDem=15}}) - \Phi(\tau_J \middle| \text{ChallWin}^*_{\text{Xmean,ChallDem=15}})\right\}\\ &\quad -\left\{\Phi(\tau_{J-1} \middle| \text{ChallWin}^*_{\text{Xmean,ChallDem=5}}) - \Phi(\tau_J \middle| \text{ChallWin}^*_{\text{Xmean,ChallDem=5}})\right\}\end{aligned}$$

```
help estsimp       help setx      help simqi
setx chaldemc 15 defdemoc 10 audresq4 ((15-10)*.206) relres4 .206
simqi
simqi , fd(pr) changex(chaldemc 5 15 audresq4 (-5*.206) (5*.206))
```