**Data accessed originally from: http://users.ox.ac.uk/~ball0144/research.htm

**These files create the results and figures reported in Finding Pathways, Chapter7

set more off

**Creating Figure 7.1

histogram sxp, percent

set more off

** To compute the difference in predicted probability with and without the key independent variable: primary resource exports

*** Begin with a Replication of Table 3, column 1 from Collier and Hoeffler, Guns and Grievance

logit warsa c.sxp#c.sxp coldwar secm gyl peace prevwar mount geogia frac lnpop

**predict probability of war for each case

predict warSXP

**estimate the same regression, but WITHOUT the primary exports variable

logit warsa coldwar secm gyl peace prevwar mount geogia frac lnpop

**predict probability of war for each case using the prior regression

predict warwoSXP

**Generate our measure of Expected Relationship; the difference between the predicted probability with and without the key explanatory variable

** positive values will mean that the probability was higher with the key variable than without it.

gen diffwarSXPwoSXP = warSXP - warwoSXP

** Using the data we can now create the relevant figures used in case selection

twoway (scatter diffwarSXPwoSXP sxp if sxp<1 & warsa==1, msymbol(x) legend(off)) ///
(scatter diffwarSXPwoSXP sxp if sxp<1 & warsa==0) ///
Replication of Table 3, column 1 from Collier and Hoeffler, Guns and Grievance

logit warsa c.sxp##c.sxp coldwar secm gy1 peace prevwar mount georgia frac lnpop

*note that the regression above uses a different syntax, but estimates the same regression they did. I use an interaction term to take account of the squared stuff

**to compute the marginal effects:

margins, at(sxp=(.002 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8 .85 .9 .95 1.0)) atmeans vsquish post

marginsplot
marginsplot, noci

*Now, let's graph the effects

forvalues i=1/21 {
    mat t[`i',1] = _b[`i'._at]                      /* get probability estimates */
    mat t[`i',2] = _b[`i'._at] - 1.96*_se[`i'._at]  /* compute lower limit */
    mat t[`i',3] = _b[`i'._at] + 1.96*_se[`i'._at]  /* compute upper limit */
}

mat t=t,a                                          /* horizontal concatenation */
svmat t, names(col)                                /* save matrix as data */

twoway (rarea ll ul at)(line prob at), legend(off)  ///
        xtitle(sxp) ytitle(probability) scheme(lean1)
clear

** TO COMPUTE THE SAME EFFECTS BUT AT MEDIAN VALUES OF Xs
use "/Users/nicholasweller/Dropbox/Weller Files/BarLer/Replication Material/Chapter 7/Chapter7replication.dta"

logit warsa c.sxp##c.sxp coldwar secm gy1 peace prevwar mount geogia frac lnpop

*note that the regression above uses a different syntax, but estimates the same
regression they did. I use an interaction term to take account of the squared stuff

**to compute the marginal effects:

margins, at(sxp=(.002 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8 .85 .9 .95
1.0)) at((median) _all) vsquish post

*Now, let's graph the effects

mat t=J(21,3,.)
mat a = (.002 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8 .85 .9 .95 .1)
/* get the 11 "at" values */

forvalues i=1/21 {
    mat t[`i',1] = _b[`i'._at]                       /* get probability estimates */
    mat t[`i',2] = _b[`i'._at] - 1.96*_se[`i'._at]   /* compute lower limit */
    mat t[`i',3] = _b[`i'._at] + 1.96*_se[`i'._at]   /* compute upper limit */
}

mat t=t,a                                          /* horizontal concatenation */
mat colnames t = prob ll ul at                     /* fix column names */
svmat t, names(col)                                /* save matrix as data */

twoway (rarea ll ul at)(line prob at), legend(off) ///
    xtitle(sxp) ytitle(probability) scheme(lean1)

clear

*BELOW COMPUTES MARGINAL EFFECTS WITH Xs SET AT 25TH PERCENTILE

use "/Users/nicholasweller/Dropbox/Weller Files/BarLer/Replication Material/Chapter 7/Chapter7replication.dta"

logit warsa c.sxp##c.sxp coldwar secm gy1 peace prevwar war mount geogia frac lnpop

*note that the regression above uses a different syntax, but estimates the same
regression they did. I use an interaction term to take account of the squared stuff

**to compute the marginal effects:

margins, at(sxp=(.002 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8 .85 .9 .95
1.0)) at((p25) _all) vsquish post

*Now, let's graph the effects

mat t=J(21,3,.)
mat a = (.002 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8 .85 .9 .95 .1)
/* get the 11 "at" values */

forvalues i=1/21 {
    mat t[`i',1] = _b[`i'._at]                       /* get probability estimates */

}
**BELOW PROVIDES MARGINAL EFFECTS AT 75TH PERCENTILE**

*note that the regression above uses a different syntax, but estimates the same regression they did. I use an interaction term to take account of the squared stuff

**to compute the marginal effects:**

```
logit warsa c.sxp##c.sxp coldwar secm gy1 peace prevwar mount geogia frac lnpop
margins, at(sxp=(.002 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8 .85 .9 .95 1.0)) at((p75) _all) vsquish post
```

*Now, let's graph the effects

```
mat a = (.002\ .05\ .1\ .15\ .2\ .25\ .3\ .35\ .4\ .45\ .5\ .55\ .6\ .65\ .7\ .75\ .8\ .85\ .9\ .95\ 1)
```

/* get the 11 "at" values */

```
forvalues i=1/21 {
    mat t[`i',1] = _b[`i'.at]                       /* get probability estimates */
    mat t[`i',2] = _b[`i'.at] - 1.96*se[`i'.at]   /* compute lower limit */
    mat t[`i',3] = _b[`i'.at] + 1.96*se[`i'.at]   /* compute upper limit */
}
```

```
twoway (rarea ll ul at)(line prob at), legend(off) ///
   xtitle(sxp) ytitle(probability) scheme(lean)
```

**clear**