Simulation of Eliminating Physical Punishment With MICS Data

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Background

What would the world look like if we eliminated physical punishment? These are some quick calculations using MICS data.

Get The Data

```
. clear all

.
. set seed 3846

.
. cd "/Users/agrogan/Desktop/newstuff/MICS-eliminate-cp"
/Users/agrogan/Desktop/newstuff/MICS-eliminate-cp

.
. use "/Users/agrogan/Box Sync/MICS/Data/MICS.dta"
```

Are we using the most *up to date* data?

Descriptive Statistics on Physical Punishment

```
. tabulate d_phys_spank
```

Selected child spanked	Freq.	Percent	Cum.
0	122,373	56.68	56.68
1	93,512	43.32	100.00
Total	215,885	100.00	

Predict Aggression With A Multilevel Model

For demonstration purposes, I am only including a *limited* set of covariates. One could–and should–easily include more although including more covariates considerably lengthens the estimation time.

```
. melogit ec16 i.d_phys_spank cmale cage || country:
Fitting fixed-effects model:
```

```
Iteration 0:   log likelihood = -142628.21
Iteration 1:   log likelihood = -142431.02
Iteration 2:   log likelihood = -142430.93
Iteration 3:   log likelihood = -142430.93

Refining starting values:

Grid node 0:   log likelihood = -135384.24

Fitting full model:

Iteration 0:   log likelihood = -135384.24  (not concave)
Iteration 1:   log likelihood = -135381.58  (backed up)
Iteration 2:   log likelihood =    -135380  (backed up)
Iteration 3:   log likelihood = -135376.47
Iteration 4:   log likelihood = -135368.83
Iteration 5:   log likelihood = -135359.89
Iteration 6:   log likelihood = -135351.72
Iteration 7:   log likelihood = -135349.08
Iteration 8:   log likelihood = -135349.08

Mixed-effects logistic regression               Number of obs     =    215,885
Group variable:         country                 Number of groups  =         62

                                                Obs per group:
                                                              min =        115
                                                              avg =    3,482.0
                                                              max =     20,451

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(3)      =    2481.66
Log likelihood = -135349.08                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
        ec16 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
1.d_phys_spank |   .3466554   .0094956    36.51   0.000     .3280443    .3652665
       cmale |   .3010048   .0092288    32.62   0.000     .2829166    .3190929
        cage |  -.0060204    .000674    -8.93   0.000    -.0073415   -.0046993
       _cons |  -.6711418   .0895672    -7.49   0.000    -.8466903   -.4955932
-------------+----------------------------------------------------------------
country      |
   var(_cons)|   .4282121   .0778397                      .2998671    .6114895
------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 14163.72    Prob >= chibar2 = 0.0000
```

Estimate Margins (Predicted Probabilities of Aggression)

```
. margins d_phys_spank // predicted probabilities of aggression

Predictive margins                              Number of obs     =    215,885
Model VCE    : OIM

Expression   : Marginal predicted mean, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
d_phys_spank |
           0 |   .3251464   .0169289    19.21   0.000     .2919665    .3583264
           1 |   .3979304   .0182745    21.78   0.000     .3621131    .4337478
------------------------------------------------------------------------------
```

Calculations

One could rely on commands such as the one below to do these calculations *on-the-fly*.

```
. * matrix b = r(b) // get matrix of results
.
. * matrix list b  // list it out to double check
```

In this example, however, I have hand-coded the calculations, so the calculations may need to be rewritten every time more covariates are added to the model. On the other hand, writing out the calculations explicitly likely increases the transparency of the thought process below.

In a hypothetical sample of 100 children…

Aggressive Children Among Not Spanked Children

proportion not spanked $*$ proportion aggressive $*$ 100

```
. display round(.5668 * .3251464  * 100)
18
```

Not Aggressive Children Among Not Spanked Children

number not spanked $-$ number aggressive

```
. display 57 - 18
39
```

Aggressive Children Among Spanked Children

proportion spanked $*$ proportion aggressive $*$ 100

```
. display round(.4332 * .3979304 * 100)
17
```

Not Aggressive Children Among Spanked Children

number spanked $-$ number aggressive

```
. display 43 - 17
26
```

Number Aggressive Children Among Spanked Children If They Were Not Spanked

```
. display round(.4332 * .3251464  * 100)
14
```

Reduction in Number of Aggressive Children

```
. display 17 - 14 // this many fewer aggressive children / 100
3
```

Graph (*DRAFT*)

Is this the best graph?

I note that only 3 children in the graph below change their status; on the other hand this is 3 children out of 17 total children displaying aggression or a $\frac{3}{17} \approx 18\%$ reduction in aggression.

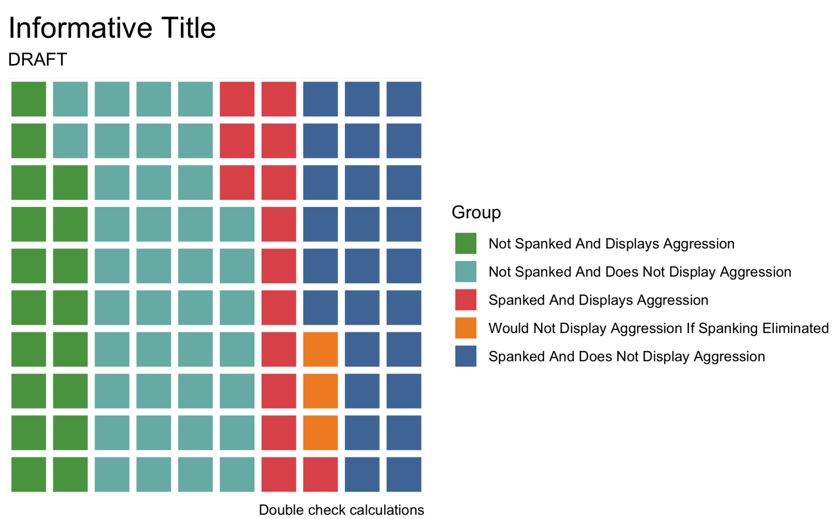

Figure 1: Graph