Visualizing Multilevel Models

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Table of contents

1 Introduction

An evolving set of notes on visualizing results from multilevel models.

The examples below use the `simulated_multilevel_data.dta` file from *Multilevel Thinking*. Here is a direct link to download the data.

2 Organizing Questions

Try to think about some of the advantages and disadvantages of different approaches to visualizing multilevel models. In multilevel models, we don't want to just *control for* variation, but to start to *explore* the variation. Put concretely:

- Some approaches use *dots*. Some approaches use *lines*. Some approaches use *dots and lines*.
- Some approaches use the *raw unadjusted* data. Other approaches use *adjusted or model predicted* data.
- Some approaches attempt to show the *Level 2 specific regression lines*; some approaches only show an *average regression line*.
- What approaches might work well with *large numbers* of Level 2 units? What approaches might work well with *smaller numbers* of Level 2 units?

What approach(es) do you prefer?

3 Setup

I am not terrifically fond of the default `s2color` graph scheme in earlier versions of Stata. Here I make use of the `michigan` graph scheme available at: https://agrogan1.github.io/Stata/michigan-graph-scheme/

```
set scheme michigan
```

Stata's `s1color` scheme would also would be an option as would be Asjad Naqvi's incredible `schemepack`: https://github.com/asjadnaqvi/stata-schemepack.

Throughout the tutorial, I make frequent use of the `mcolor(%30)` option to add some visual interest to scatterplots by adding transparency to the markers.

4 Get Data

```
use "https://github.com/agrogan1/multilevel-thinking/raw/main/simulate-and-analyze-multile
```

```
note:
      https://github.com/agrogan1/multilevel-thinking/raw/main/simulate-and-a
      > nalyze-multilevel-data/simulated_multilevel_data.dta redirected to
      https://raw.githubusercontent.com/agrogan1/multilevel-thinking/main/sim
      > ulate-and-analyze-multilevel-data/simulated_multilevel_data.dta
```

5 Scatterplots (`twoway scatter y x`)

```
twoway scatter outcome warmth, mcolor(%30)

graph export myscatter.png, width(1500) replace
```

```
file myscatter.png saved as PNG format
```

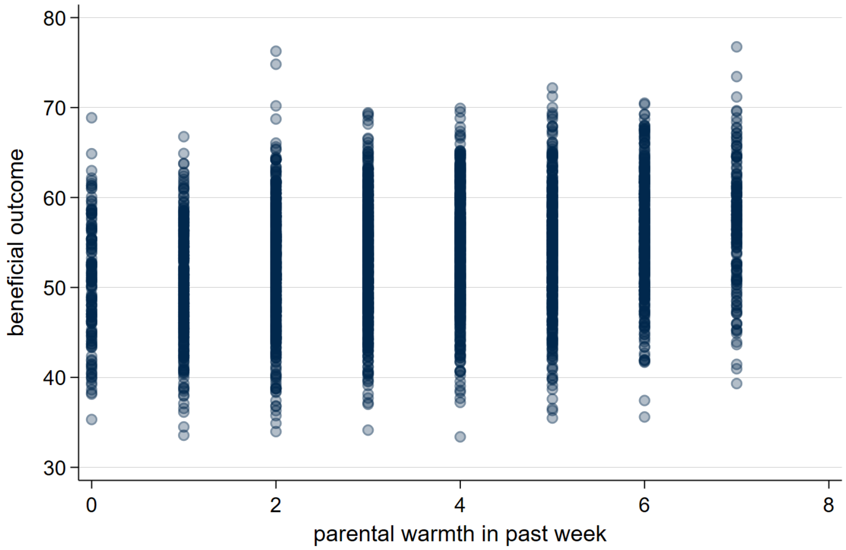


Figure 1: Scatterplot

6 Simple Linear Fit (`twoway lfit y x`)

```
twoway lfit outcome warmth

graph export mylinear.png, width(1500) replace
```

```
file mylinear.png saved as PNG format
```

7 Linear Fit With Confidence Interval (`twoway lfitci y x`)

```
twoway lfitci outcome warmth

graph export mylfitci.png, width(1500) replace
```

```
file mylfitci.png saved as PNG format
```

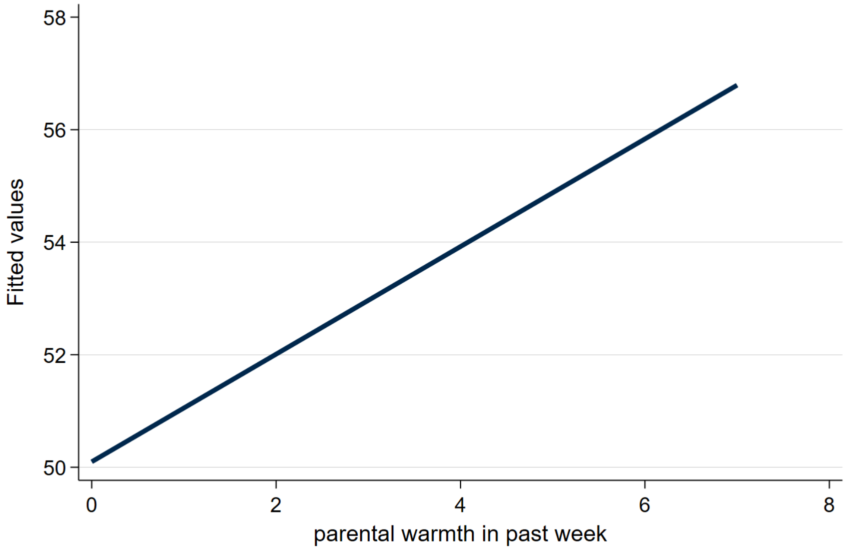


Figure 2: Linear Fit

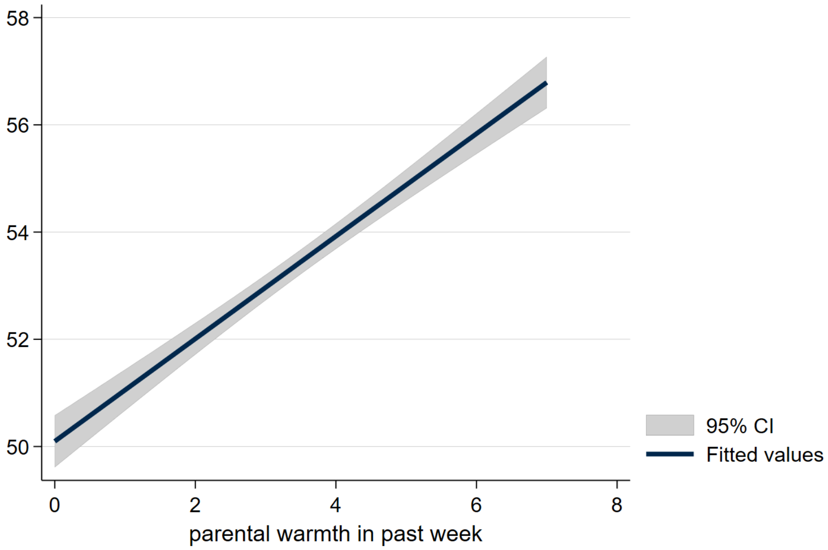


Figure 3: Linear Fit With Confidence Interval

8 Combine Scatterplot and Linear Fit (twoway (scatter y x) (lfit y x))

```
twoway (scatter outcome warmth, mcolor(%30)) (lfit outcome warmth)

graph export myscatterlinear.png, width(1500) replace
```

```
file myscatterlinear.png saved as PNG format
```

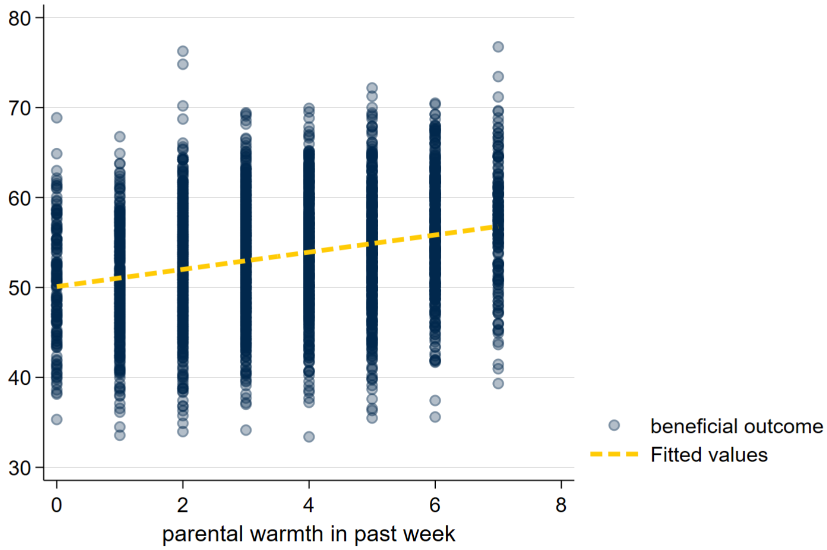


Figure 4: Scatterplot and Linear Fit

9 Spaghetti Plots (spagplot y x, id(group))

```
spagplot outcome warmth, id(country)

graph export myspaghetti.png, width(1500) replace
```

```
file myspaghetti.png saved as PNG format
```

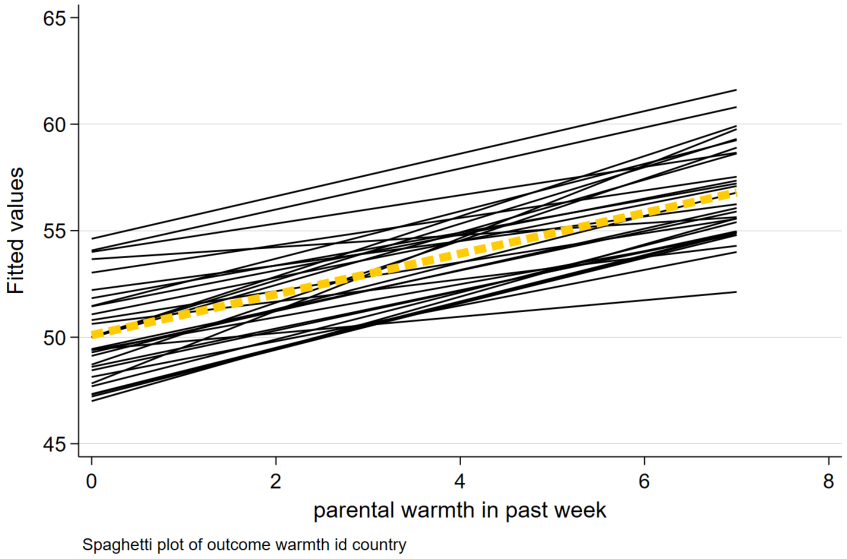


Figure 5: Spaghetti Plot

10 Small Multiples (`twoway y x, by(group)`)

Small Multiples, showing a separate graph for each group in the data, are an increasingly popular data visualization technique. Below, I build a small multiples graph using the `by` option in Stata. I use the `aspect` option to adjust the *aspect ratio* of the graph for better visual presentation.

```
twoway (scatter outcome warmth, mcolor(%30)) ///
(lfit outcome warmth), ///
by(country) aspect(1)

graph export mysmallmultiples.png, width(1500) replace
```

```
file mysmallmultiples.png saved as PNG format
```

11 Taking A Random Sample

At times, we may have *too many* Level 2 units to effectively display them on a *spaghetti plot*, or using *small multiples*. If this is the case, we may need to *randomly sample* Level 2 units.

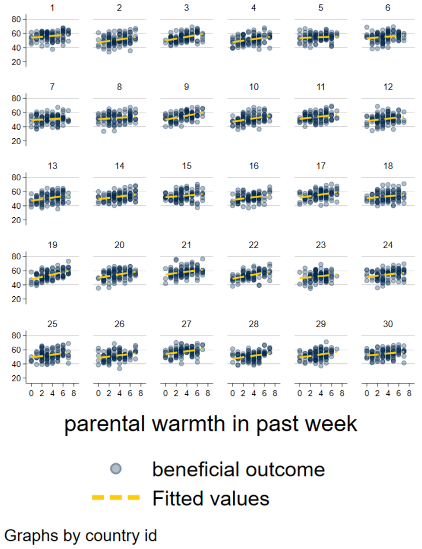


Figure 6: Small Multiples

This can be difficult to accomplish as our standard `sample` command operates on each row, or on Level 1 units.

We can accomplish random sampling at Level 2, with a little bit of code.

```
set seed 3846 // random seed for reproducibility

gen randomid = runiform() // generate a random id variable

* by country (i.e. by Level 2 unit) replace the randomid
* with the first randomid for that country (Level 2 unit)
* so that every person in that country has the same random id

bysort country: replace randomid = randomid[1]

summarize randomid // descriptive statistics for random id

twoway (scatter outcome warmth, mcolor(%30)) /// scatterplot
(lfit outcome warmth) /// linear fit
if randomid < .5, /// only use a subset of randomids
by(country) aspect(1) // by country
```

```
graph export mysmallmultiples2.png, width(1500) replace
```

```
(2,970 real changes made)

    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
    randomid |      3,000    .6174022    .2374704   .0733026   .9657055


file mysmallmultiples2.png saved as PNG format
```

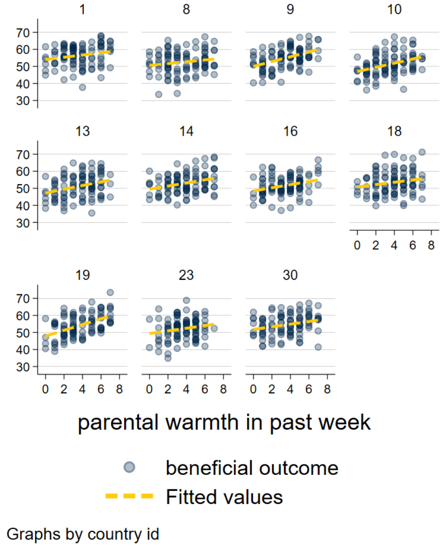


Figure 7: Small Multiples With A Random Sample Of Countries

12 Multivariate (Predicted) Relationships

A sometimes unacknowledged point is that graphs–unless we take steps to correct this–reflect *unadjusted*, or *bivariate* associations. We may sometimes wish to develop a graphs that reflect the *adjusted* or *predicted* estimates from our models.

In multilevel models, *prediction* is a complex question. Prediction may–or may not–incorporate the information from the random effects. The procedures below outline graphs that incorporate predictions using the random effects, by using the `predict ..., fitted` syntax.

12.1 Using Predicted Values (`predict`)

`predict` generates a predicted value for *every observation in the data.*

12.1.1 Estimate The Model

```
mixed outcome warmth physical_punishment i.group || country: // estimate MLM
```

```
Performing EM optimization Performing gradient-based optimization:
Iteration 0:  Log likelihood = -9668.0859
Iteration 1:  Log likelihood = -9668.0859

Computing standard errors ...

Mixed-effects ML regression                          Number of obs    =  3,000
Group variable: country                              Number of groups =     30
                                                     Obs per group:
                                                                  min =    100
                                                                  avg =  100.0
                                                                  max =    100
                                                     Wald chi2(3)     = 401.00
Log likelihood = -9668.0859                          Prob > chi2      = 0.0000

------------------------------------------------------------------------------
     outcome | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      warmth |    .961837   .0581809    16.53   0.000     .8478046    1.075869
physical_p~t |  -.8457672   .0798128   -10.60   0.000    -1.002197   -.6893369
     2.group |   1.084409   .2200548     4.93   0.000     .6531099    1.515709
       _cons |   51.64797   .4645466   111.18   0.000     50.73748    52.55847
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
country: Identity            |
                  var(_cons) |      3.403   .9717558      1.944438    5.955659
-----------------------------+------------------------------------------------
               var(Residual) |   36.01911   .9346952      34.23295    37.89847
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 200.29        Prob >= chibar2 = 0.0000
```

12.1.2 Generate Predicted Values

```
predict outcome_hat, fitted // predict yhat (`fitted` uses fixed AND random effects)
```

12.1.3 Graph With `twoway` Syntax

```
twoway (scatter outcome_hat warmth, mcolor(%30)) (lfit outcome_hat warmth)

graph export mypredictedvalues.png, width(1500) replace

twoway (lfit outcome_hat warmth)

graph export mypredictedvalues2.png, width(1500) replace
```

```
file mypredictedvalues.png saved as PNG format


file mypredictedvalues2.png saved as PNG format
```

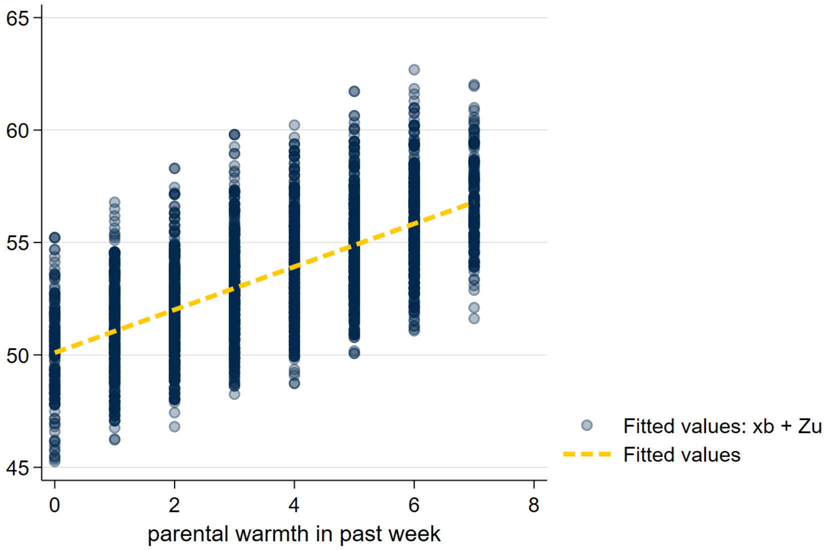


Figure 8: Predicted Values From `predict`

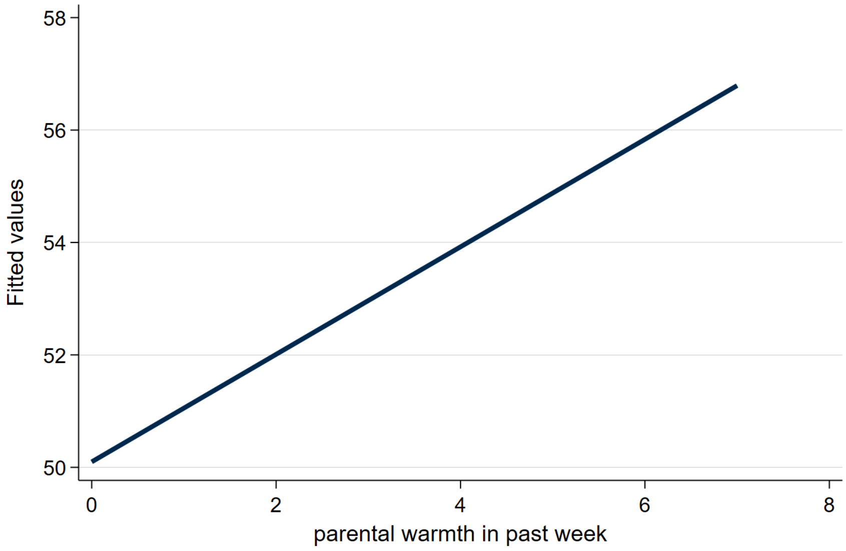


Figure 9: Predicted Values From `predict` With Only Linear Fit

12.1.4 Spaghetti Plot With Predicted Values

```
spagplot outcome_hat warmth, id(country)

graph export myspaghetti2.png, width(1500) replace
```

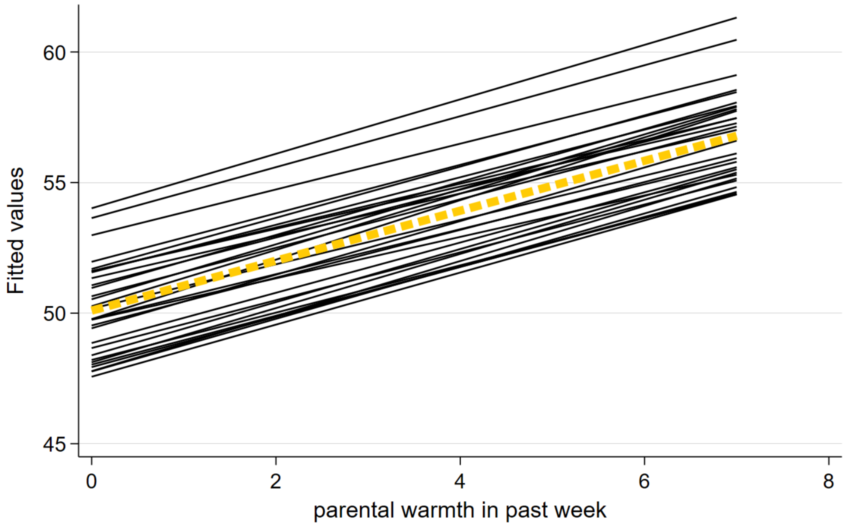
```
file myspaghetti2.png saved as PNG format
```

12.2 `margins` and `marginsplot`

In contrast to `predict`, which generates a predicted value for *every observation in the data*, `margins` generates predicted values at *specific values of certain variables*.

12.2.1 Estimate The Model

```
mixed outcome warmth physical_punishment i.group || country: // estimate MLM
```



Spaghetti plot of outcome_hat warmth id country

Figure 10: Spaghetti Plot With Predicted Values

```
Performing EM optimization Performing gradient-based optimization:
Iteration 0:   Log likelihood = -9668.0859
Iteration 1:   Log likelihood = -9668.0859

Computing standard errors ...

Mixed-effects ML regression                          Number of obs     =  3,000
Group variable: country                              Number of groups =      30
                                                     Obs per group:
                                                                  min =     100
                                                                  avg =   100.0
                                                                  max =     100
                                                     Wald chi2(3)      = 401.00
Log likelihood = -9668.0859                          Prob > chi2       = 0.0000

------------------------------------------------------------------------------
     outcome | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      warmth |    .961837   .0581809    16.53   0.000     .8478046    1.075869
physical_p~t |  -.8457672   .0798128   -10.60   0.000    -1.002197   -.6893369
     2.group |   1.084409   .2200548     4.93   0.000     .6531099    1.515709
       _cons |   51.64797   .4645466   111.18   0.000     50.73748    52.55847
------------------------------------------------------------------------------
```

```
------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
country: Identity            |
                  var(_cons) |      3.403   .9717558      1.944438    5.955659
-----------------------------+------------------------------------------------
               var(Residual) |   36.01911   .9346952      34.23295    37.89847
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 200.29        Prob >= chibar2 = 0.0000
```

12.2.2 Generate Predicted Values *At Specified Values* With `margins`

```
margins group, at(warmth = (1 2 3 4 5 6 7)) // predictive *margins*
```

```
Predictive margins                                       Number of obs = 3,000

Expression: Linear prediction, fixed portion, predict()
1._at: warmth = 1
2._at: warmth = 2
3._at: warmth = 3
4._at: warmth = 4
5._at: warmth = 5
6._at: warmth = 6
7._at: warmth = 7

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   _at#group |
        1 1  |    50.4999   .3983539   126.77   0.000     49.71914    51.28066
        1 2  |   51.58431   .3994365   129.14   0.000     50.80143    52.36719
        2 1  |   51.46174   .3809288   135.10   0.000     50.71513    52.20834
        2 2  |   52.54615     .38173   137.65   0.000     51.79797    53.29432
        3 1  |   52.42357    .371884   140.97   0.000      51.6947    53.15245
        3 2  |   53.50798   .3723656   143.70   0.000     52.77816    54.23781
        4 1  |   53.38541   .3718315   143.57   0.000     52.65664    54.11419
        4 2  |   54.46982   .3719738   146.43   0.000     53.74077    55.19888
        5 1  |   54.34725   .3807751   142.73   0.000     53.60094    55.09355
        5 2  |   55.43166   .3805823   145.65   0.000     54.68573    56.17759
        6 1  |   55.30909    .398109   138.93   0.000     54.52881    56.08937
        6 2  |    56.3935    .397607   141.83   0.000      55.6142    57.17279
        7 1  |   56.27092   .4228024   133.09   0.000     55.44225     57.0996
        7 2  |   57.35533   .4220306   135.90   0.000     56.52817     58.1825
------------------------------------------------------------------------------
```

12.2.3 Graph With `marginsplot`

```
marginsplot // plot of predicted values

graph export mymarginsplot.png, width(1500) replace
```

```
Variables that uniquely identify margins: warmth group

file mymarginsplot.png saved as PNG format
```

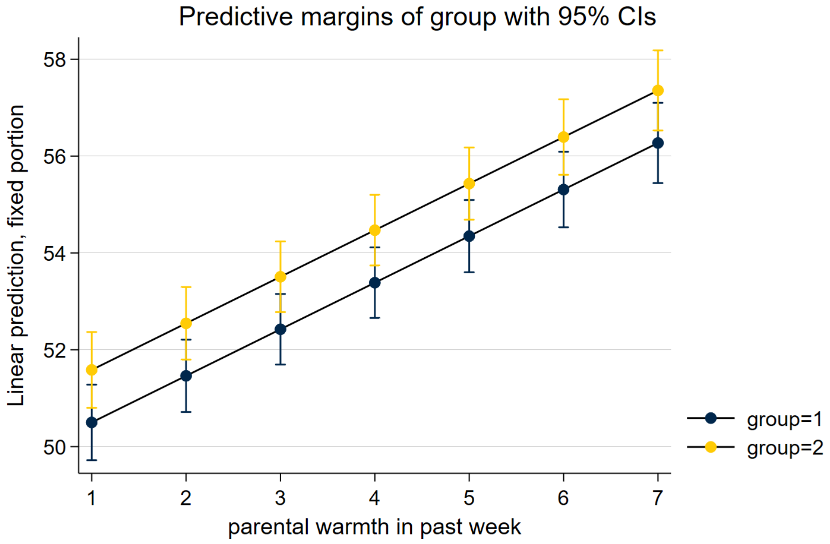


Figure 11: Predicted Values From `margins` and `marginsplot`

13 Scatterplot With Linear Fit and Marginal Density Plots (`twoway ...`)

As another possibility, we may wish to show more of the variation, by showing the variation in the *independent* variable and the *dependent* variable along with a *scatterplot* and *linear fit*. This is a complex graph and requires a little bit of manual programming in Stata.

> You could also investigate the user written program `binscatterhist` (`ssc install binscatterhist`) which produces a similar looking graph, and automates much of this work.

13.1 Manually Generate The Densities To Plot Them Below (`kdensity ...`)

> We generate the density for *warmth* at only a few points (`n(8)`) since this variable has relatively few categories.

```
kdensity warmth, generate(warmth_x warmth_d) n(8) // manually generate outcome densities

kdensity outcome, generate(outcome_y outcome_d) // manually generate outcome densities
```

13.2 Rescale The Densities So They Plot Well

> You may have to experiment with the scaling and moving factors.

```
replace warmth_d = 100 * warmth_d // rescale the density so it plots well

replace outcome_d = 5 * outcome_d - .5 // rescale AND MOVE the density so it plots well

label variable outcome_y "density: beneficial outcome" // relabel y variable
```

```
(8 real changes made)

(50 real changes made)
```

13.3 Make The Graph (`twoway ...`)

> You may have to experiment with whether scatterplots or line plots work best for displaying the x and y densities.

```
twoway (scatter outcome warmth, mcolor(%10)) /// scatterplot w some transparency
(lfit outcome warmth) /// linear fit
(line warmth_d warmth_x) /// line plot of x density
(line outcome_y outcome_d), /// line plot of y density (note flipped order)
title("Outcome by Warmth") /// title
ytitle("beneficial outcome") /// manual ytitle
xtitle("parental warmth") /// manual xtitle
legend(position(6) rows(2) ) /// legend at bottom; 2 rows
xlabel(0 1 2 3 4 5 6 7) /// manual x labels
name(mynewscatter, replace)

graph export mynewscatter.png, width(1500) replace
```

```
file mynewscatter.png saved as PNG format
```

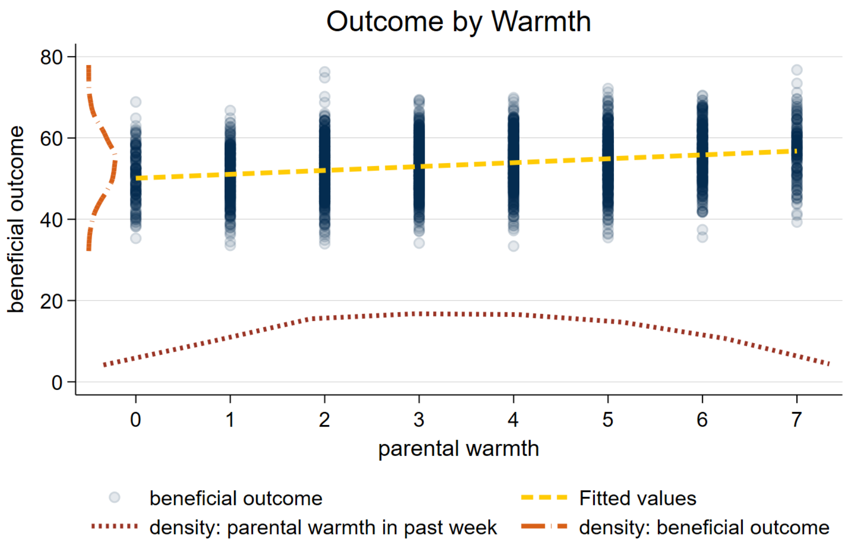


Figure 12: Scatterplot and Linear Fit With Marginal Density Plots

13.4 Spaghetti Plot With Linear Fit and Marginal Density Plots

14 Curvilinear and Linear Fits

15 Random Effects