Visualizing Multilevel Models

Andy Grogan-Kaylor

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Introduction

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

> When this document is presented in *slide show format*, some slides may be long, and you may need to *scroll down* to see the full slide. In slide show format use the left and right arrow keys to navigate through the slides. `b` will make the text bigger. `s` will make the text smaller.

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

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?

Setup

I am not terrifically fond of Stata's default `s2color` graph scheme. Therefore 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

Get Data

```
. use "https://github.com/agrogan1/multilevel-thinking/raw/main/simulate-and-analyze-m
> ultilevel-data/simulated_multilevel_data.dta", clear
```

Scatterplots

```
. twoway scatter outcome warmth

. graph export myscatter.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/myscatter.png saved as
    PNG format
```

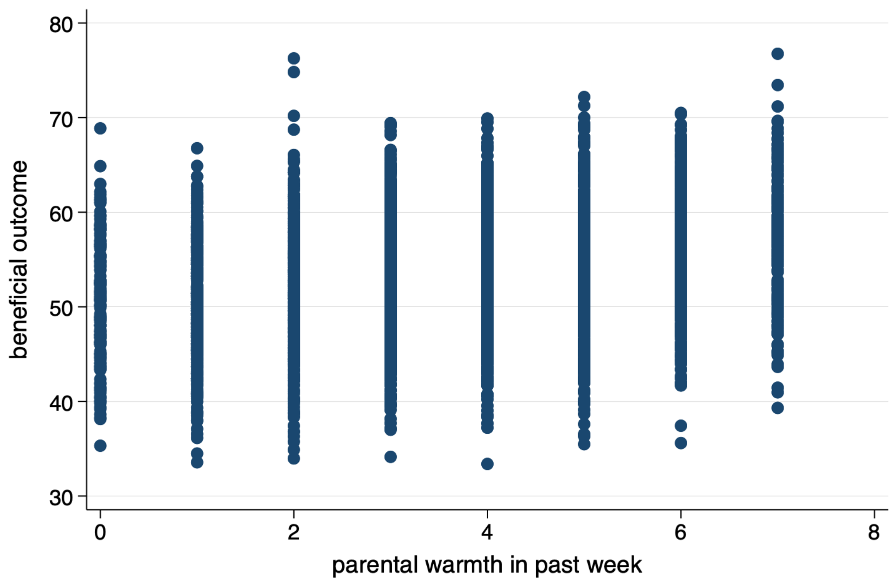


Figure 1: Scatterplot

Simple Linear Fit

```
. twoway lfit outcome warmth

. graph export mylinear.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/mylinear.png saved as
    PNG format
```

Linear Fit With Confidence Interval

```
. twoway lfitci outcome warmth

. graph export mylfitci.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/mylfitci.png saved as
    PNG format
```

Combine Scatterplot and Linear Fit

```
. twoway (scatter outcome warmth) (lfit outcome warmth)

. graph export myscatterlinear.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/myscatterlinear.png
    saved as PNG format
```

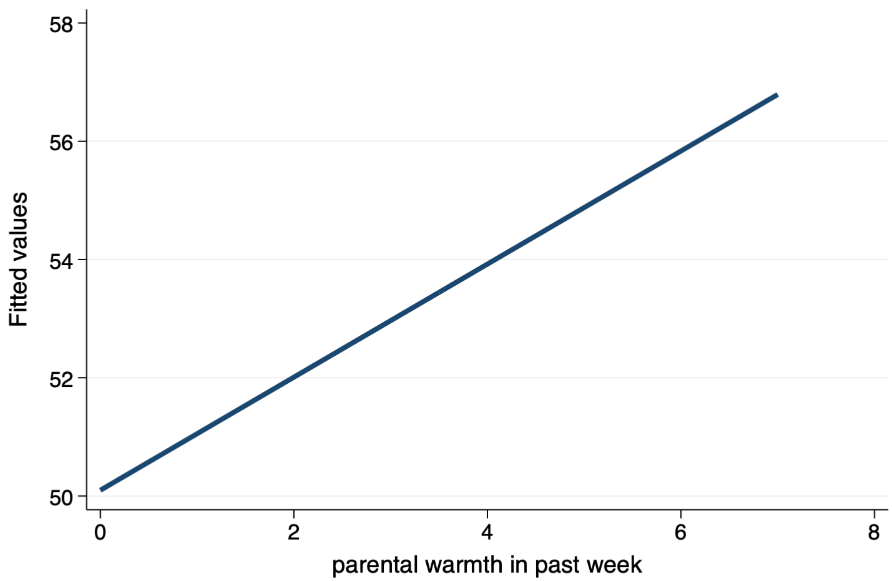


Figure 2: Linear Fit

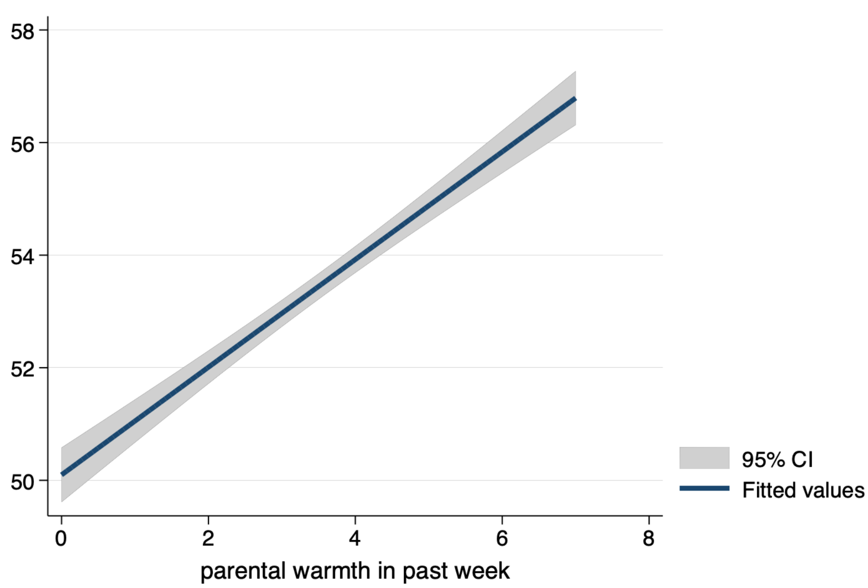


Figure 3: Linear Fit With Confidence Interval

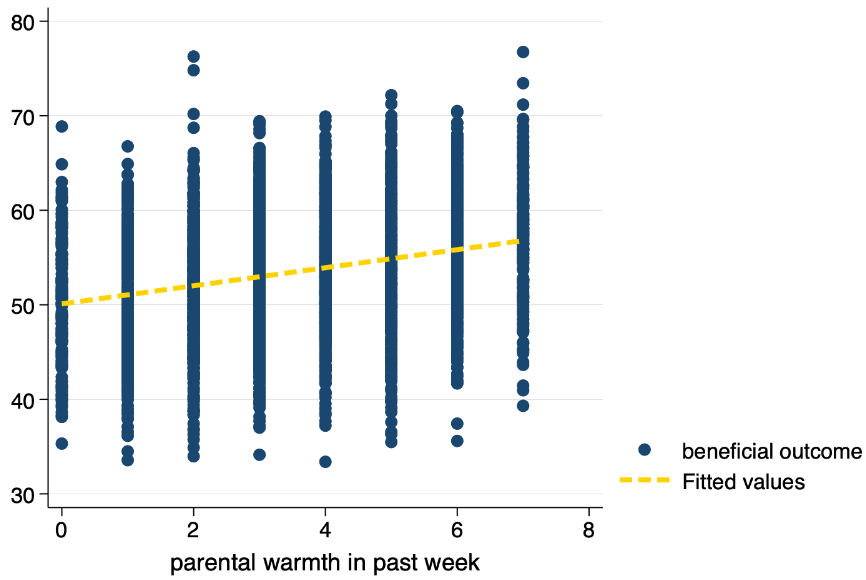


Figure 4: Scatterplot and Linear Fit

Spaghetti Plots (`spagplot`)

```
. spagplot outcome warmth, id(country)

. graph export myspaghetti.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/myspaghetti.png saved
    as PNG format
```

Small Multiples

I use the `aspect` option to adjust the *aspect ratio* of the graph for better visual presentation. I also use the `mcolor(%30)` option to create some transparency in the dots of the scatterplot, which helps the presentation of these small multiples. The `mcolor(%30)` option could be useful in the other graphs in this tutorial as well.

```
. twoway (scatter outcome warmth, mcolor(%30)) (lfit outcome warmth), by(country) aspe
> ct(1)

. graph export mysmallmultiples.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/mysmallmultiples.png
    saved as PNG format
```

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. The procedures below outline graphs that incorporate predictions using the variables, but do not include predictions that incorporate the random effects. (This will be added!)

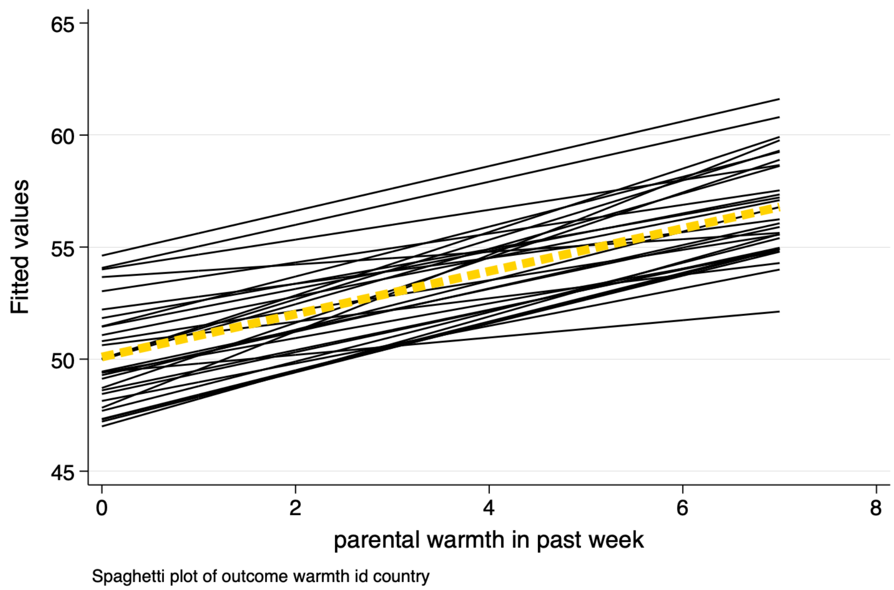


Figure 5: Spaghetti Plot

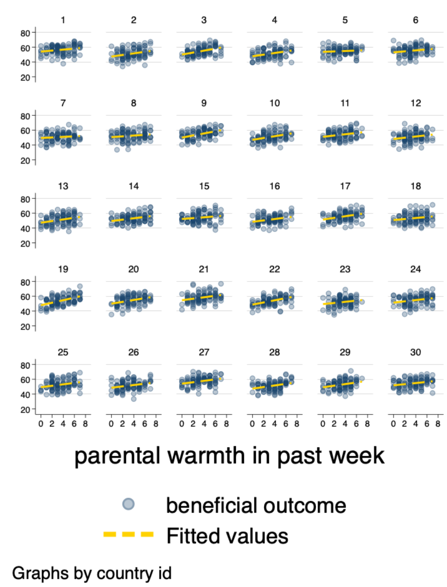


Figure 6: Small Multiples

Using Predicted Values

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_punishment |  -.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
```

Generate Predicted Values

```
. predict outcome_hat // predict yhat
(option xb assumed)
```

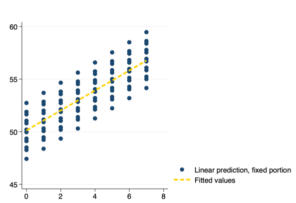
Graph With twoway Syntax

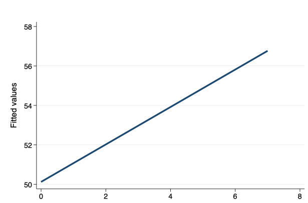
```
. twoway (scatter outcome_hat warmth) (lfit outcome_hat warmth)

. graph export mypredictedvalues.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/mypredictedvalues.png
    saved as PNG format

. twoway (lfit outcome_hat warmth)

. graph export mypredictedvalues2.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/mypredictedvalues2.png
    saved as PNG format
```





Spaghetti Plot With Predicted Values

```
. spagplot outcome_hat warmth, id(country)

. graph export myspaghetti2.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/myspaghetti2.png saved
    as PNG format
```

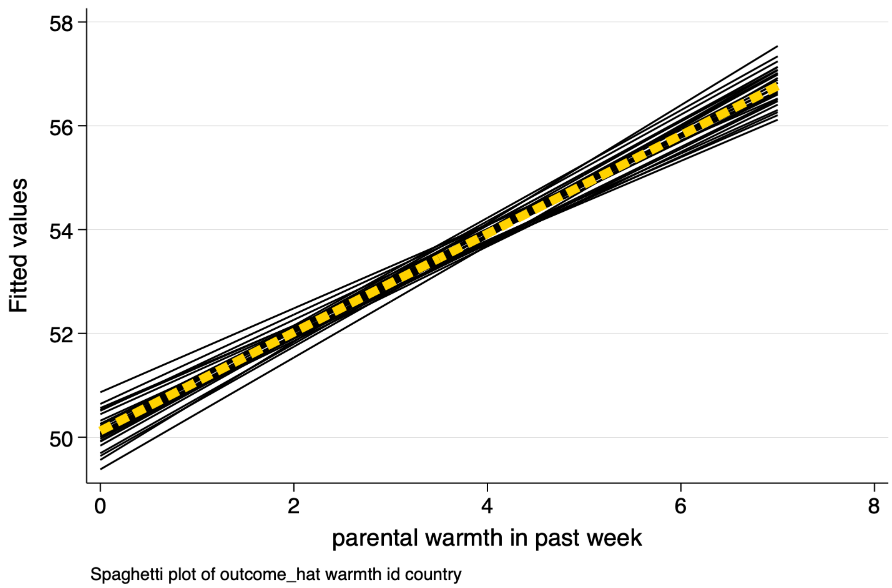


Figure 7: Spaghetti Plot With Predicted Values

`margins` and `marginsplot`

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_punishment	-.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
```

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
```

	Margin	Delta-method 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

Graph With `marginsplot`

```
. marginsplot // plot of predicted values

Variables that uniquely identify margins: warmth group

. graph export mymarginsplot.png, width(1500) replace
file /Users/agrogan/Desktop/GitHub/multilevel/visualizing-MLM/mymarginsplot.png
    saved as PNG format
```

Curvilinear and Linear Fits

Random Effects

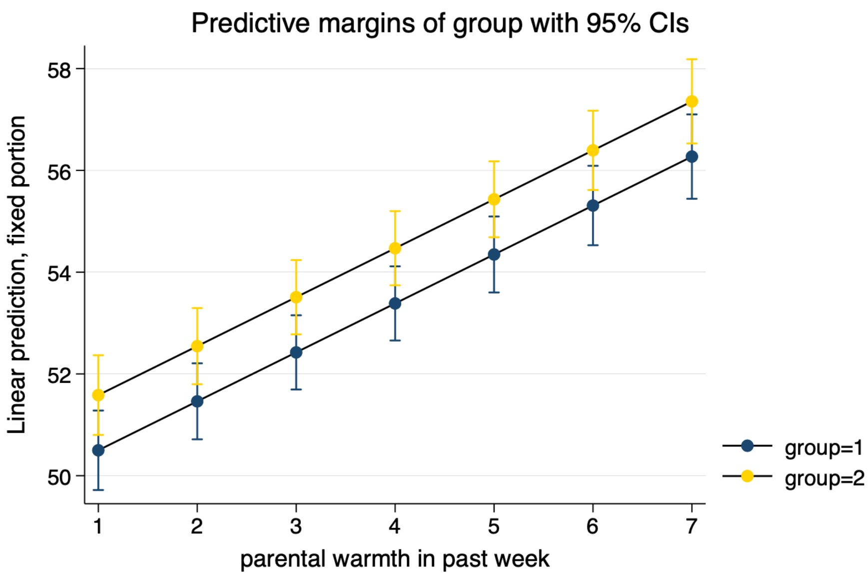


Figure 8: Predicted Values From `margins` and `marginsplot`