Polytomous Models: Multinomial Regression

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March 4, 2024

When to use...

- Your outcome variable is categorical/ nominal with **3 or more levels**
  - **Cannot be ordered or ranked in any way**
- You want to understand the relationship between predictors and the probability of the outcomes

For example...

Participants: Undergraduate students (n= 917) at a private, elite university on West coast of United States.

Data: Surveyed twice every year for all four years of college.

Social network (“Who are your closest friends?”)

- Friends Lost (cumulative nominees removed)
- Friends Gained (cumulative nominees added)
- Volatility (total number of changes to network)

Depression (CES-D scale)

Demographic characteristics

Depression Trajectories: Classified CES-D into 5 trajectories.

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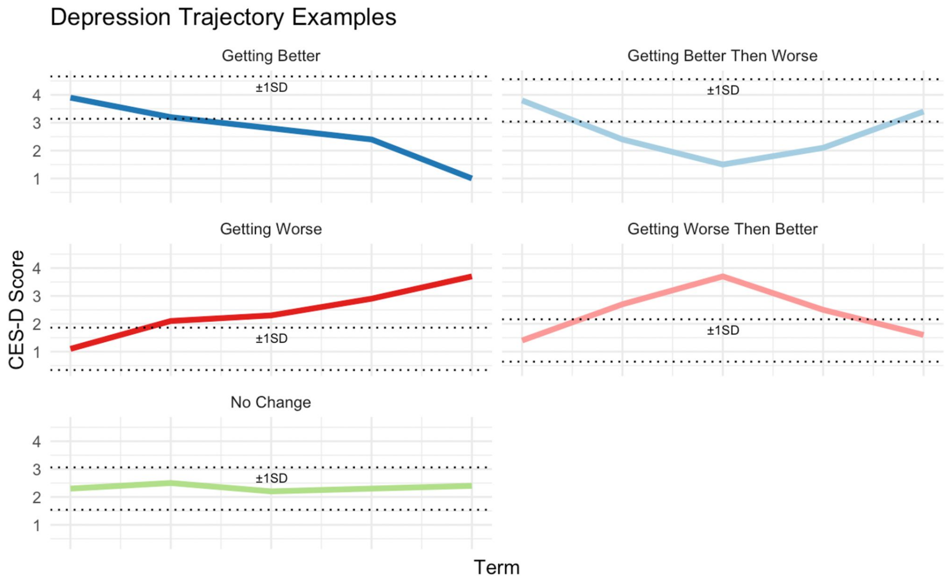
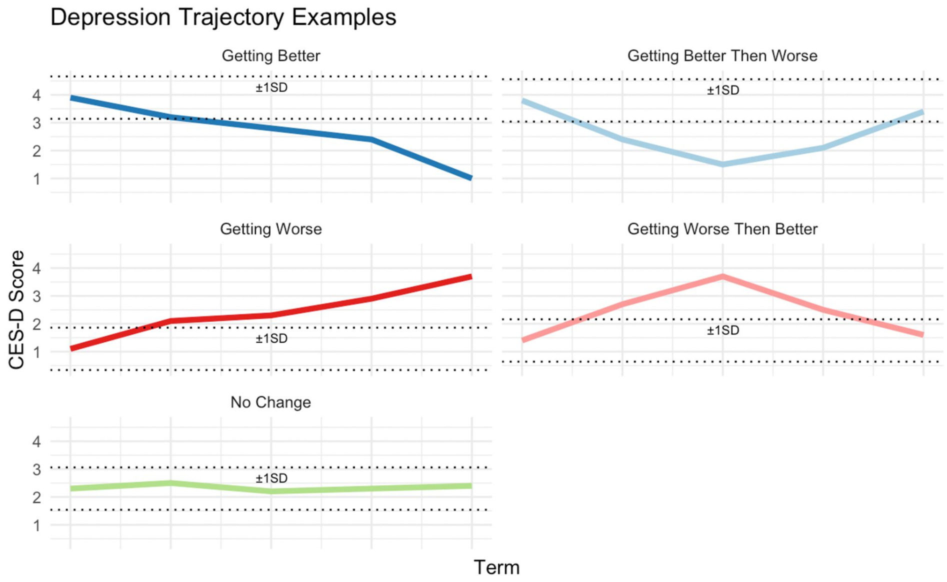


For example...

Can friendship volatility predict which depression trajectory a student falls into?

- Outcome var: depression trajectory categories (5)
- Predictor var: friends lost, friends gained, or friend volatility



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- Independence of observations
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- No assumption of normality or heteroskedasticity

Option 1: Stratified Model

Treat the categories as independent binomial logistic regressions!

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```
data <- df %>%
  dplyr::select(group, TotalVolatility) %>%
  filter(group == "getting better" | group == "getting worse") %>%
  mutate(group = case_when(
    group == "getting better" ~ 1,
    group == "getting worse" ~ 0,
    TRUE ~ NA_integer_
  ))

fit1 <- glm(group ~ TotalVolatility, family = "binomial", data = data)

tidy(fit1, conf.int = TRUE) %>%
  kable()
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term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-0.3633326	0.3175705	-1.144101	0.2525819	-0.9943893	0.2547459
TotalVolatility	0.0285714	0.0143019	1.997741	0.0457448	0.0009955	0.0572899

For each unit increase in TotalVolatility, the log-odds of getting better as opposed to getting worse increases by 0.0285714.

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Option 2: Multinomial Logistic Regression

- A series of binomial models comparing the **reference category** to each of the other categories
- Runs a generalized linear model on the log-odds of each category versus the reference category
    - Reference category = “getting worse”
    - [“getting worse” vs “getting better”], [“getting worse” vs “getting better then worse”], [“getting worse” vs “getting worse then better”], [“getting worse” vs “flat”]

Option 2: Multinomial Logistic Regression

```
fit2 <- multinom(formula=group ~ TotalVolatility * CESD.timeOne +
degree_CF.timeOne, data=df, family="binomial")
```

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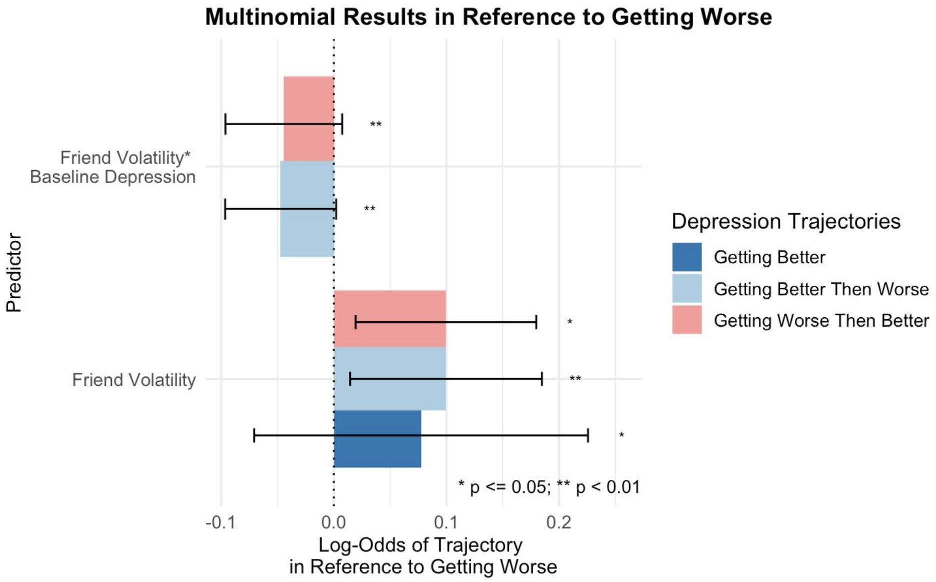

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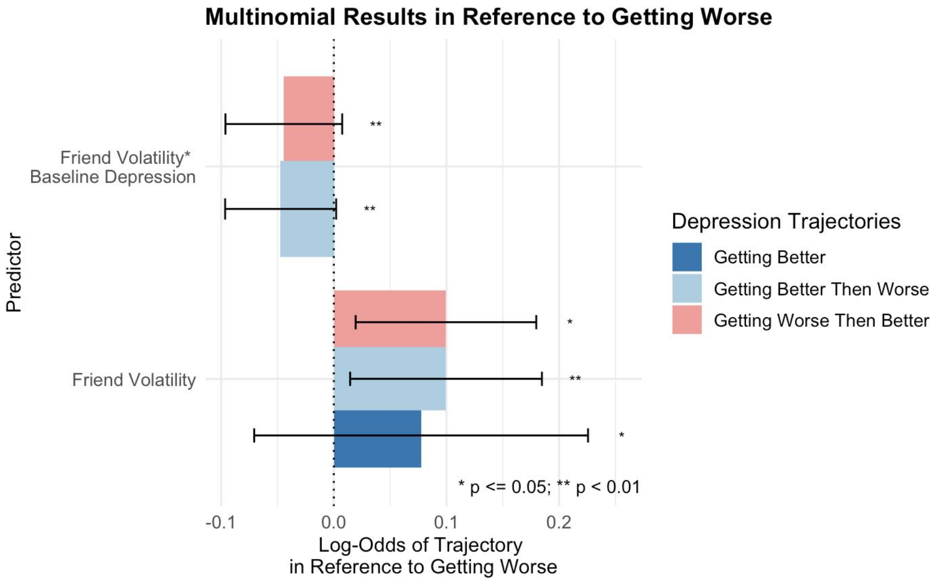

Coefficients = the change in the log odds of having one of these depression trajectories (compared to "getting worse") for a one-unit change in friendship volatility.

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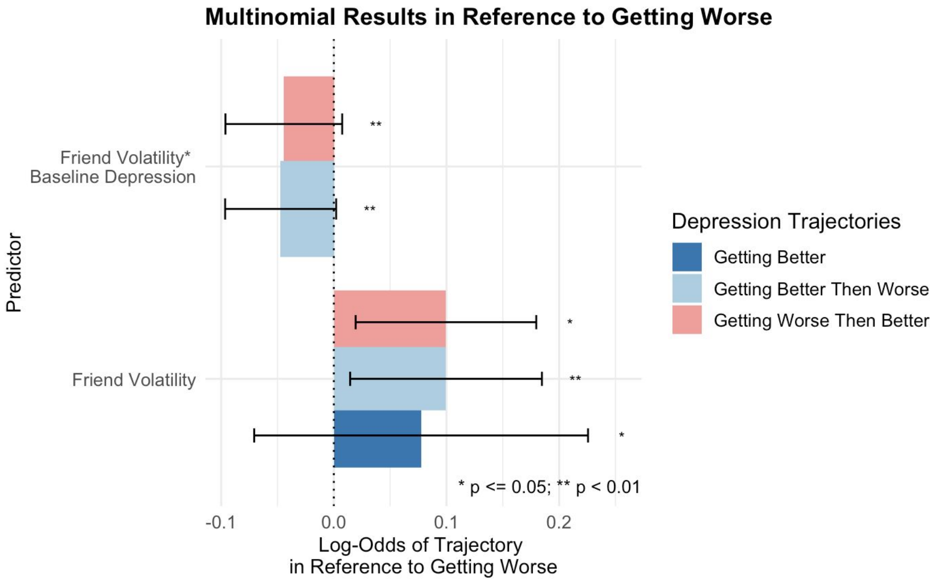

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→ calculate odds ratios and probabilities

- Odds greater than 1 indicate the event is more likely to occur than the reference event, while odds less than 1 indicate it is less likely.

Changing the Reference

What if you want to look at other categories?

- e.g. What are the odds ratios of “Getting Better” (B) relative to “Getting Better then Worse” (C)?

Two options:

1. Change the reference category and rerun your analyses!
2. Calculate the difference between the coefficients of B and C against A (“Getting Worse”)