

Latent Growth Factors as Predictors of Distal Outcomes

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@McCormickNeuro



<https://mccormickneuro.github.io/>

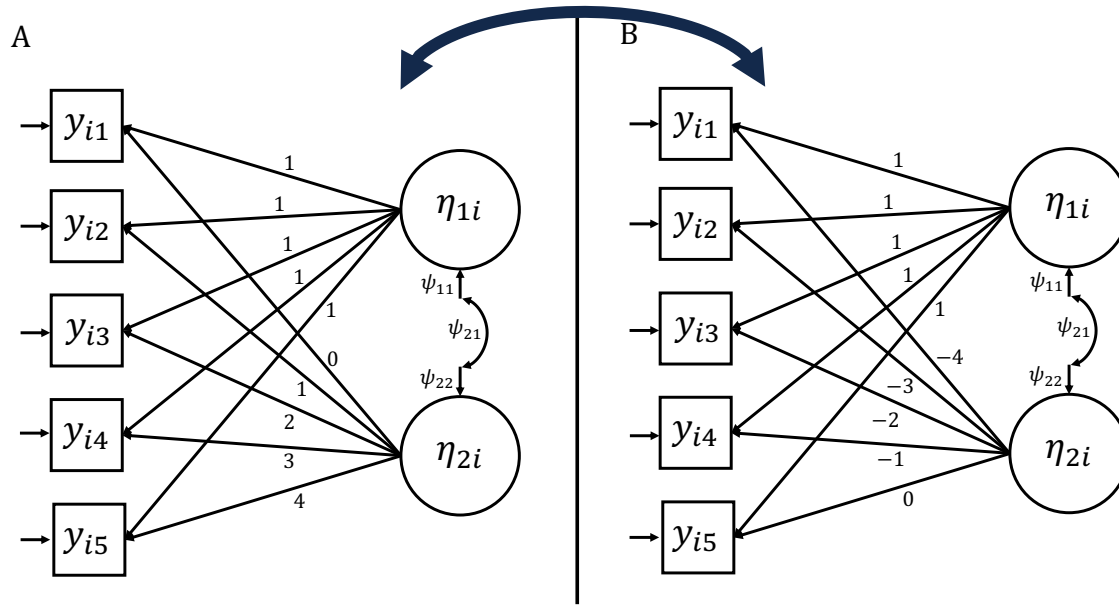


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Introduction

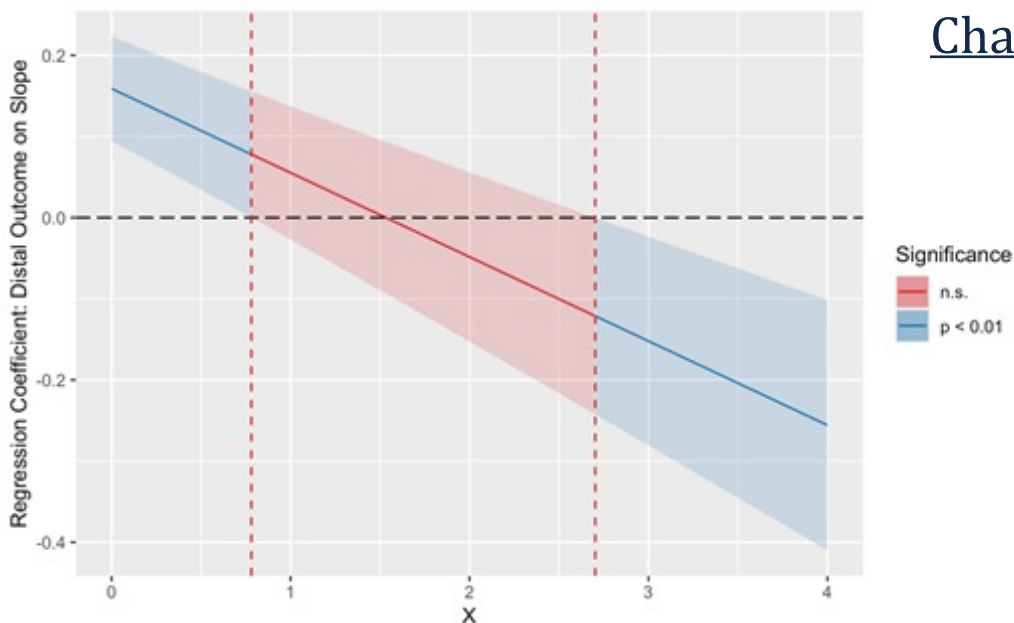
- We have well-developed tools for modeling unconditional growth models and predictors of the growth factors¹
 - Much less work has been done on using the parameters of this growth model to predict distal outcomes
- We can put our intercept anywhere within the timeline and the model fits exactly the same²
 - Known parameter transformations between models²

Equivalent Models



Time-Coding Effects with Distal Outcomes

- When including a distal outcome, the parameter change for the effect of the slope on the outcome changes linearly
 - Can become non-significant or even reverse sign
 - An “invisible” problem for substantive researchers
- Can calculate an “aperture” point³ to make slope regression maximally interpretable



Change in Effect of Slope on Distal Outcome

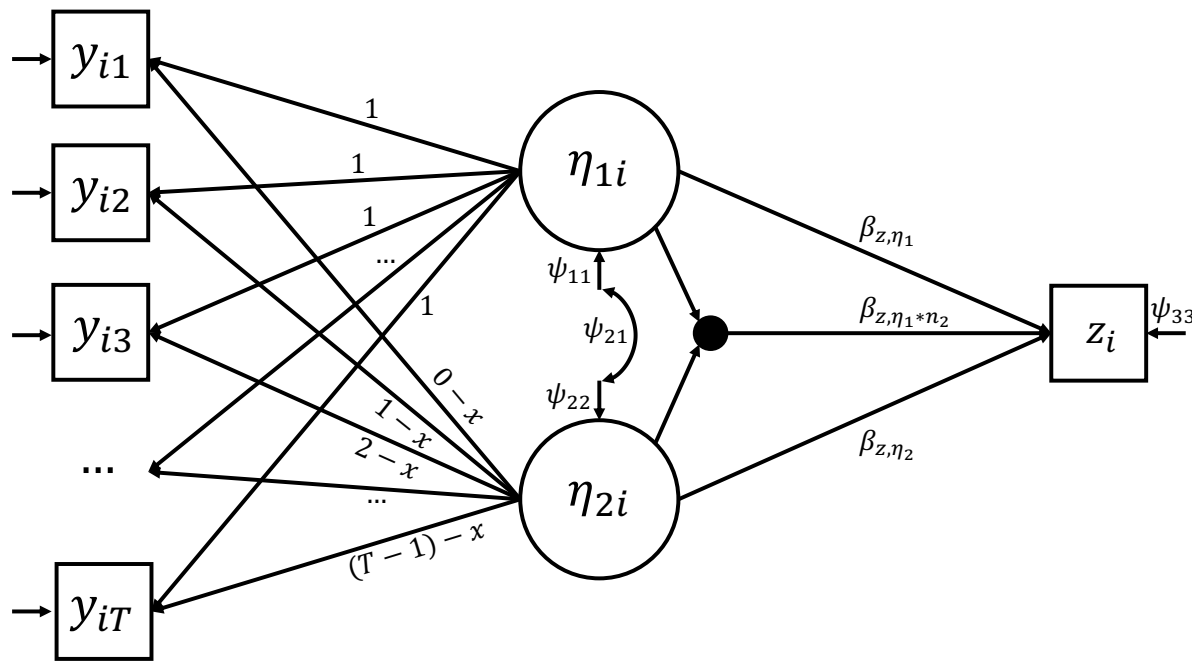
$$\leftarrow \beta_{z, \eta_2}^* = \beta_{z, \eta_2} - \beta_{z, \eta_1} \Delta x$$

Aperture Shift

$$x = - \frac{\psi_{\eta_1, \eta_2}}{\psi_{\eta_2}}$$

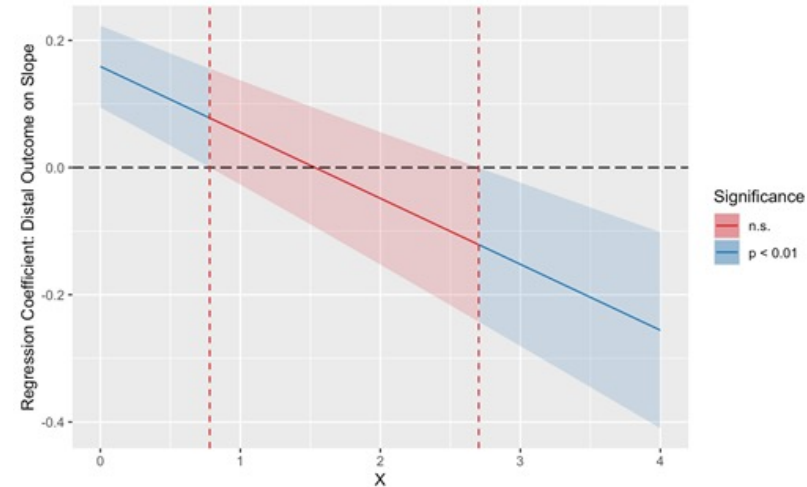
Main Effects Vs. Interactions

- A main effects model estimates the slope effect “above and beyond” the intercept effect
 - Conceptually ill-posed since both terms are estimated on the same data
 - Want to use the trajectory information as a whole
 - Categorical approach ➡ growth mixture model⁴
 - Continuous approach ➡ latent interaction model⁵



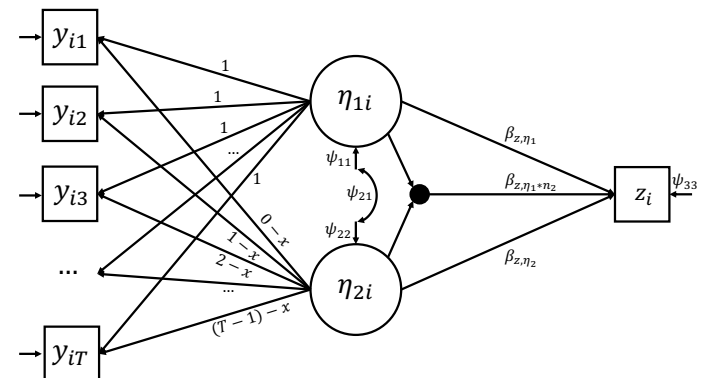
Discussion: Three main innovations

- Extended time-coding effect + SEs derivations to growth models with distal outcomes
 - Intercept effect does not change but slope effect does
- Introduced aperture point to maximize interpretability
 - Minimize covariance of the intercept and slope
- Use latent interactions to consider joint effects instead of only main effects



Aperture Shift Parameter

$$x = - \frac{\psi_{\eta_1, \eta_2}}{\psi_{\eta_2}}$$



References

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Acknowledgements

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- Patrick Curran
- Gregory Hancock



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