Examining Nonlinear Science Achievement Growth Using Early Childhood Longitudinal Study-Kindergarten: 2011

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Much of the extant literature in achievement studies employs linear models, which assume that students' growth occurs at a constant rate over an extended period. Although other growth modeling approaches are often used to capture nonlinear growth, such as higher order polynomials (e.g., quadratic, cubic) and mixtures with different growth trajectories, interpretation of such models is often intractable substantively (e.g., Kirk, 2013). Researchers have underscored the need in formulating nonlinear models that can more fully examine the total change experienced, the rate of change as well as the timing of peak change that are more compatible with the learning curves in educational theories (Blozis & Harring, 2016; Preacher & Hancock, 2015). The present study leverages a national representative sample consisting of 18,174 children from 1,310 elementary schools in the United States where data were collected biannually during kindergarten and fifth grade. The final data set consisted of 2,916 students with appropriate strata, PSU, and longitudinal weights applied to optimally handle the nonresponse missing data. Compared to the earlier ECLS-K:1998 study, ECLS-K:2011 is advantageous in aptly assessing the rapid developmental changes occurring between ages 5 and 7 years, commonly known as the 5-to-7-year shift (Sameroff & Haith, 1996). Science achievement scores were vertically linked item-response- theory scaled scores that allows us to make clear inferences about the shape of growth across time. In sum, this study aims to (1) apply a statistical technique that has been relatively underemployed—Gompertz growth modeling in the domain of science learning from kindergarten through fifth grade; and (2) examine the dynamic relations between science literacy instruction and achievement growth by adding time-varying predictors. Our subsequent analyses will include a wider range of covariates including school level contextual variables to better understand the micro- and meso-factors impacting children's science achievement growth.

References

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