**Supplemental Material**

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**I. Selection of Analytic Approach and Results of Alternative Approach**

We selected the time-structured approach to longitudinal modeling (i.e., binning children by age) as our primary analytic approach due to several perceived drawbacks of the individually-varying times of observation approach. Most notably, with three observation points (i.e., three years of assessment), using individually-varying times of observation limited us to looking at linear trajectories (Bollen & Curran, 2006), which was inappropriate based on visual inspection of the delay discounting data. Second, models with individually-varying times of observation only yield comparative fit indices (e.g., AIC, BIC). They do not produce absolute fit indices (e.g., chi-square test, CFI/TLI, or RMSEA), so assessing absolute model fit is more difficult than with time-structured models (Muthén & Muthén, 1998-2012). Finally, when using individually-varying times of observation for the latent trajectory models (LCGAs), there is no VLMR LRT produced to compare the k class model to the k-1 class model, which makes decisions about the number of classes more arbitrary.

Despite the perceived advantages of the time-structured approach, we wanted to ensure that our results were not due to arbitrarily binning children into age groups, so we repeated analyses for the stop signal reaction time and working memory models using individually-varying times of observation. (We do not report these for the delay discounting models because, as noted, this approach is not appropriate to capture the non-linear trends evident in the raw data.)

Reassuringly, the individually-varying times of observation are highly similar to those using the age-structured approach. Results of the LCM models replicated with nearly identical magnitude intercept and slope estimates in both approaches (**Table S1**). The LCGAs in the typically-developing sample also yielded highly similar 2-class solutions using both analytic approaches (**Table S2 for parameter estimates and S3 for fit statistics**).

In the ADHD sample, LCGA models for stop signal RT indicated that BIC was lowest for the 3-class model using individually-varying times of observation (rather than the 2-class solution selected using the primary time-structured approach); however, the 3rd class included less than 1% of the sample and was difficult to interpret and so the 2-class model was identified as the most appropriate model for the data as is standard in the literature (Ram & Grimm, 2009). The two classes matched those identified using the time-structured approach (**Table S4**).

For working memory LCGA models in the ADHD sample, the 2- and 3-class models differed by exactly 10 points, which is the most commonly recommended cutoff for determining that one model fits “significantly” better than another (Raftery, 1995). Thus, evidence was equivocal to decide between these models. The 3 classes identified using individually-varying times of observation include “Stably Impaired,” “Impaired, Recovering,” and “High Working Memory” groups similar to those using the time-structured approach, where available statistical tests indicated that the 3-class model fit significantly better than the 2-class model.

Together, analyses using individually-varying times of observation increased our confidence that our primary results are not driven by or substantially limited by selection of age bins, while using that approach gives us more tools for model evaluation as noted.

*Table S1.* Results from conditional latent growth curve models for the neurocognitive measures using individually-vary times of observation (n=734)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Stop Signal Reaction Time |  |  | Working Memory |  |
|   | Estimate | SE |  |  | Estimate | SE |  |
|  Intercept | 258.44\*\* | 8.27 |  |  | 3.90\*\* | .22 |  |
|  Slope (linear) | -10.98\*\* | 2.20 |  |  | .48\*\* | .07 |  |
| Direct Effects |  |  |  |  |  |  |  |
|  ADHD diagnosis → Intercept | 59.32\*\* | 12.62 |  |  | -.70\*\* | .24 |  |
|  ADHD diagnosis → Slope | -2.88 | 3.18 |  |  | -.15\* | .05 |  |
| Covariances |  |  |  |  |  |  |  |
|  Intercept with Slope |  -927.60\* | 380.98 |  |  | .09 | .17 |  |
| BIC for linear model | 17886.74 |  |  | 7498.85 |  |
| BIC for quadratic model | 17906.87 |  |  | 7514.43 |  |

*Table S2.* Fit statistics for selection of LCGA model with individually-varying times of observation

|  |  |  |  |
| --- | --- | --- | --- |
|   | Stop Signal Reaction Time |   | Working Memory |
|   | ADHD | Controls | ADHD | Controls |
|   | BIC |  | BIC |  | BIC |  | BIC |  |
| 1 Class | 11137.61 |  | 6353.20 |  | 4262.03 |  | 2589.33 |  |
| 2 Classes | 11023.81 |  | 6314.93 |  | 4194.97 |  | 2548.90 |  |
| 3 Classes | 11001.40 |  | 6320.89 |  | 4205.44 |  | 2551.62 |  |
| 4 Classes | error |  | 6333.21 |  | 4215.93 |  | 2566.15 |  |

*Table S3.* Results of best-fitting LCGAs in typically-developing sample using individually-vary times of observation

|  |  |  |
| --- | --- | --- |
|  | Stop Signal Reaction Time | Working Memory |
|  | Class 1 | Class 2 | Class 1 | Class 2 |
|  | “Normally Developing” (*n* = 260) | “Impaired” (*n* = 7) | “Normally Developing” (*n* = 197) | “Impaired”(*n =* 69) |
|   | Estimate | SE | Estimate | SE | Estimate | SE | Estimate | SE |
|  Intercept | 238.43\*\* | 6.62 | 496.23\*\* | 28.42 | 4.31\*\* | 0.27 | 2.34\*\* | 0.46 |
|  Slope | -7.49\*\* | 1.73 | -41.84\*\* | 4.80 | .53\*\* | 0.07 | 0.27+ | 0.15 |
| Direct Effects |  |  |  |  |  |  |  |  |
|  Child Sex → Intercept | -4.98\*\* | .00 | -4.98\*\* | .00 | 0.18 | 0.36 | 0.18 | 0.36 |
|  Child Sex → Slope | 1.71\*\* | .01 | 1.71\*\* | .01 | 0.03 | 0.11 | 0.03 | 0.11 |
| % males | 51.33% | 28.57% | 50.97% | 43.48% |

*Table S4.* Results of best-fitting LCGAs in ADHD sample using individually-vary times of observation

|  |  |  |
| --- | --- | --- |
|  | Stop Signal Reaction Time | Working Memory |
|  | Class 1“Impaired” | Class 2“Unimpaired” | Class 1“Stably Impaired” | Class 2“Unimpaired” | Class 3“Impaired & Recovering” |
|  | (*n* = 70) | (*n* = 371) | (*n* = 258) | (*n =* 14) | (*n =* 181) |
|   | Estimate | SE | Estimate | SE | Estimate | SE | Estimate | SE | Estimate | SE |
|  Intercept | 481.66\*\* | 30.74 | 271.11\*\* | 7.56 | 2.49\*\* | .29 | 7.75\*\* | 1.04 | 3.42\*\* | .58 |
|  Slope | -26.36\* | 11.78 | -9.62\*\* | 1.61 | .32\*\* | .08 | -.74+ | .39 | .71\*\* | .12 |
| Direct Effects |  |  |  |  |  |  |  |  |  |  |
|  ADHD Medication → Intercept | -.96\*\* | .00 | -.96\*\* | .00 | -.10 | .33 | -.10 | .33 | -.10 | .33 |
|  ADHD Medication → Slope | 2.87\*\* | .00 | 2.87\*\* | .00 | -.12 | .11 | -.12 | .11 | -.12 | .11 |
|  Child Sex → Intercept | -22.04\*\* | .00 | -22.04\*\* | .00 | -.82\* | .41 | -.82\* | .41 | -.82\* | .41 |
|  Child Sex → Slope | 2.92\*\* | .00 | 2.92\*\* | .00 | .30\* | .14 | .30\* | .14 | .30\* | .14 |
| % males | 68.57% | 70.01% | 68.60% | 85.71% | 70.17% |

*Table S5.*Table of Fit Statistics for LCM Models using time-structured analyses

|  |  |  |  |
| --- | --- | --- | --- |
|   |  |   |  |
|   | Stop Signal Reaction Time | Working Memory | Delayed Reward Discounting |
|   | Linear  | Quadratic  | Linear  | Quadratic  | Linear | Quadratic | Piecewise Linear |
| χ2 Value | 30.90 *p* = .32 | 18.13, *p* = .75 | 26.07, *p* = .57 | 24.72, *p* = .48 |  |  | 0.00, *p* = 1.00 |
| CFI | .99 | 1.00 | 1.00 | 1.00 |  | 1.00 |
| TLI | .99 | 1.03 | 1.01 | 1.00 |  | 1.00 |
| RMSEA | .01 | .00 | .00 | .00 |  | .00 |

*Note*: In the case of the delay reward discounting model, neither the linear nor quadratic models yielded reliable results, likely because visual examination of the raw data suggests that both of these models are grossly inappropriate for modeling the trends. The piecewise linear model (with the knot defined at age 11) fit the data well, and thus was selected.

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