Online Supplemental Materials I
Generic latent change score model figure

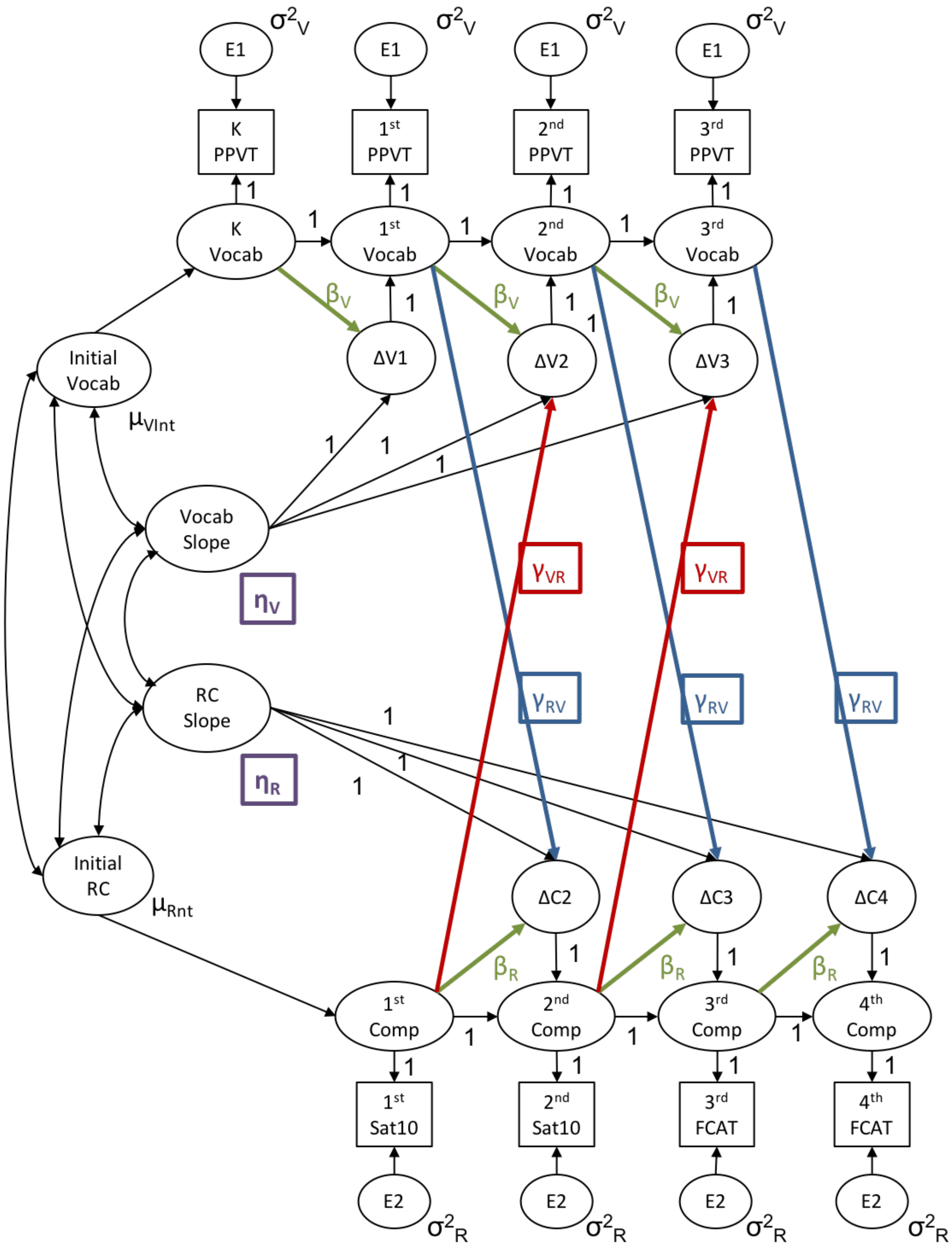

Figure S1a. Generic latent change score model figure.

Presented in ***Figure S1a*** is a generic latent change score model figure. The latent variables at each time are indicated perfectly (at 1) by the measured variables at that time. This allows the true score to be separated from an error term (E1, E2). The error terms are constrained over time as a form of measurement invariance. Additionally, and not picture in the figure, the intercepts of each latent variable are constrained to zero and their variances are constrained to 1.

Change is a function of three independent sources: constant change (η), proportional change term (β), and the cross-lagged change (γ). Constant change, represented by a slope term, gives the amount of expected time-point-to-time-point change. The proportional change coefficient indicates the level of carry-over effect specific to individuals; i.e., it estimates individual differences in how previous levels of an ability or skill influence the change in that ability or skill (auto-regression). Cross-lagged terms estimate if one variable is a leading indicator of change in the second variable.

We estimated four models with differing theoretical questions regarding the existence of the cross-lagged pathways separately for students with and without an LD. Our first model posited bidirectional relations, i.e., the red pathways indicated that comprehension was a leading indicator of change in vocabulary knowledge (γ_{VR}), and the blue pathways indicated that vocabulary knowledge was a leading indicator of change in reading comprehension (γ_{RV}). The second model removed the red pathways (by constraining their estimates to zero) and estimated only the blue pathways (vocabulary to change in reading comprehension). The third model removed the blue pathways (by constraining their pathways to zero) and estimated only the red pathways (reading comprehension to change in vocabulary). The fourth model removed both the red and blue pathways as way to estimate no cross-lagged influences.

Online Supplemental Materials II
Figures from the Multiple Group Models

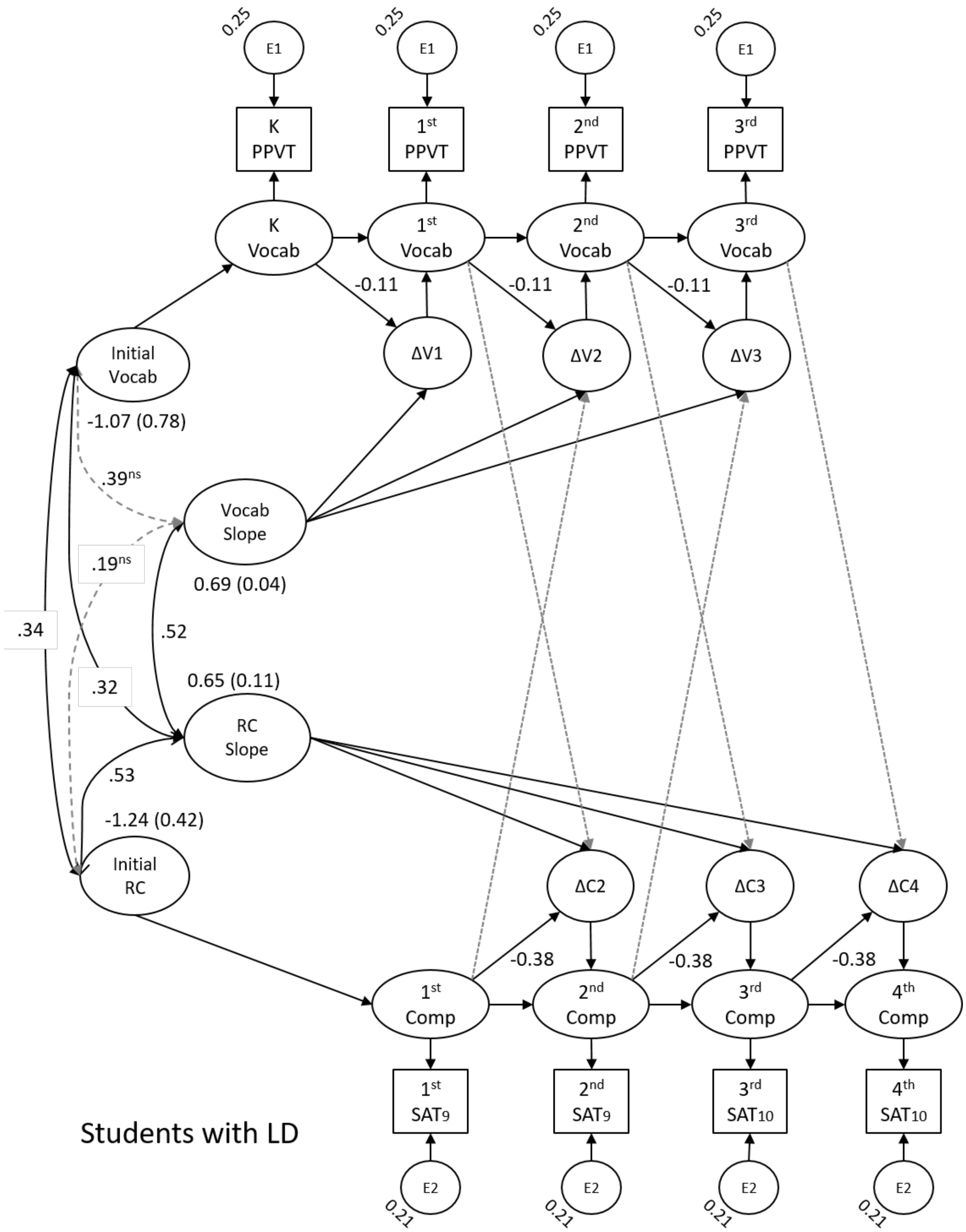

Figure S2a. Path diagram for the students with a learning disability. All parameters significant at p <.05 unless otherwise specified. Ns = not significant. Dashed lines indicate the parameter was not significant. Unmarked pathways are estimated at 1 for model identification purposes. Not pictured: within time covariances between error terms across construct (e.g., SAT9 at 1st with PPVT at 1st).

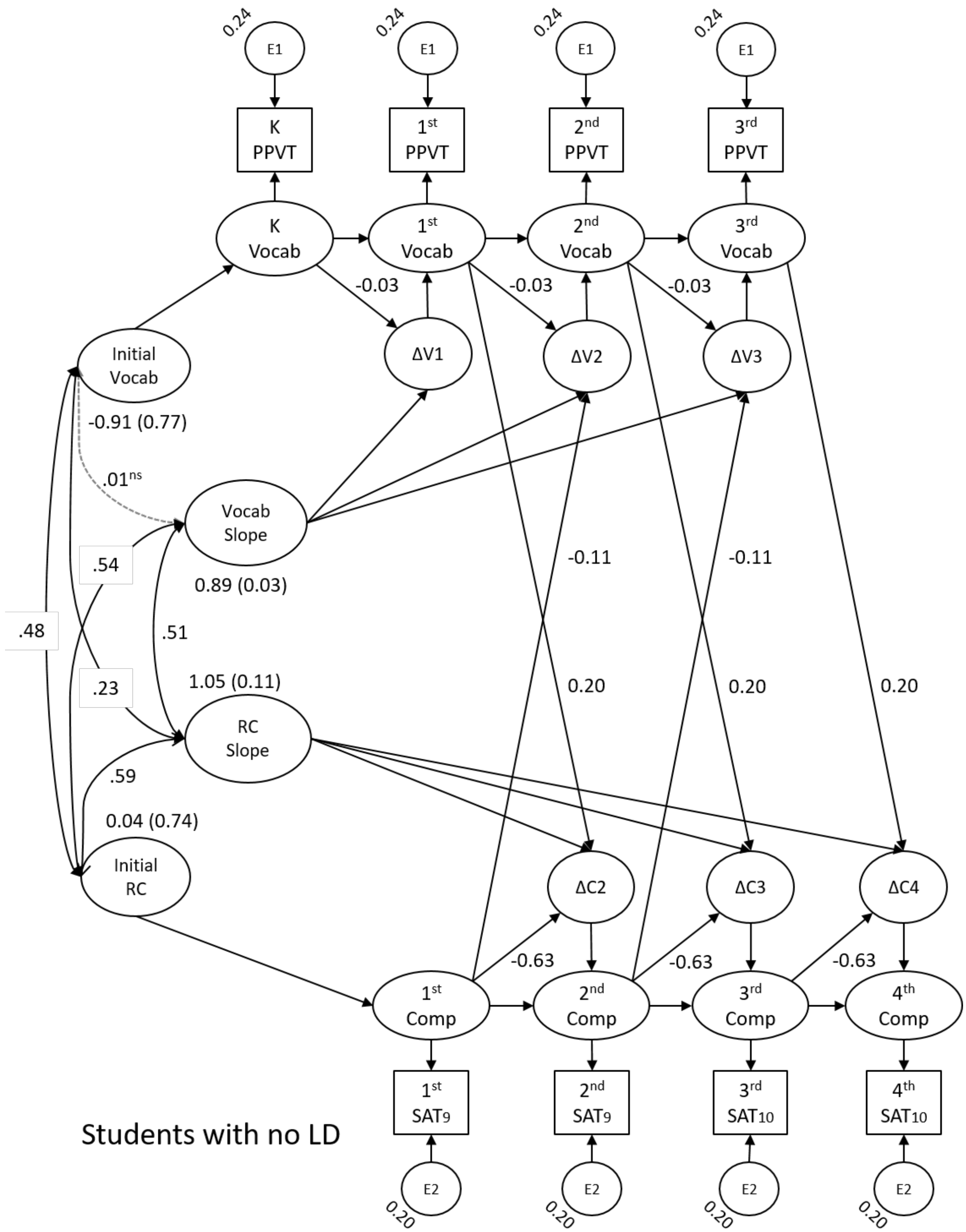

Figure S2b. Path diagram for the students with no learning disability. All parameters significant at p <.05 unless otherwise specified. Ns = not significant. Dashed lines indicate the parameter is not significant. Unmarked pathways are estimated at 1 for model identification purposes. Not pictured: within time covariances between error terms across construct (e.g., SAT9 at 1^{st} with PPVT at 1^{st}).

Online Supplemental Materials III

R Code for Manuscript Figures

Below is the code to create Figures 1-3 from the main submitted manuscript.

```
library(foreign)
library(ggplot2)
library(dplyr)
library(here)

databig<- read.spss(here('FactorScores_LONG.sav'), to.data.frame = TRUE)
dat<- read.spss(here('FactorScores_WIDE.sav'), to.data.frame = TRUE)

#### subset data ----
set.seed(3838)
ld_subset <- databig %>% filter (ESE7 == "1")
ld_IDs <- unique(ld_subset$ID)
sampled_IDs <- sample(ld_IDs, 100)
LDselect<-databig %>% filter (ID %in% sampled_IDs)

no_subset <- databig %>% filter (ESE7 == "0")
no_IDs <- unique(no_subset$ID)
nosampled_IDs <- sample(no_IDs, 100)
noselect<-databig %>% filter (ID %in% nosampled_IDs)

small<- rbind(noselect, LDselect)


####violin plot function----

GeomSplitViolin <- ggproto("GeomSplitViolin", GeomViolin,
                           draw_group = function(self, data, ..., draw_quanti
les = NULL)
                             {
  data <- transform(data,
                    xminv = x - violinwidth * (x - xmin),
                    xmaxv = x + violinwidth * (xmax - x))
  grp <- data[1,'group']
  newdata <- plyr::arrange(transform(data,
                                     x = if(grp%%2==1) xminv
                                     else xmaxv),
                           if(grp%%2==1) y
                           else -y)
  newdata <- rbind(newdata[1, ],
                   newdata,
```

```
                  newdata[nrow(newdata), ],
                  newdata[1, ])
  newdata[c(1,nrow(newdata)-1,
            nrow(newdata)), 'x']
  <- round(newdata[1, 'x'])
  if (length(draw_quantiles) > 0 & !scales::zero_range(range(data$y))) {
    stopifnot(all(draw_quantiles >= 0),
              all(draw_quantiles <= 1))
    quantiles <- ggplot2:::create_quantile_segment_frame(data,
                                                         draw_quantiles)
    aesthetics <- data[rep(1, nrow(quantiles)),
                       setdiff(names(data),
                               c("x", "y")),
                       drop = FALSE]
    aesthetics$alpha <- rep(1,
                            nrow(quantiles))
    both <- cbind(quantiles,
                  aesthetics)
    quantile_grob <- GeomPath$draw_panel(both, ...)
    ggplot2:::ggname("geom_split_violin",
                     grid::grobTree(GeomPolygon$draw_panel(newdata,
                                                           ...),
                                    quantile_grob))
  }
  else {
    ggplot2:::ggname("geom_split_violin",
                     GeomPolygon$draw_panel(newdata, ...))
  }
})

geom_split_violin <- function (mapping = NULL,
                               data = NULL,
                               stat = "ydensity",
                               position = "identity",
                               ...,
                               draw_quantiles = NULL,
                               trim = TRUE,
                               scale = "area",
                               na.rm = FALSE,
                               show.legend = NA,
                               inherit.aes = TRUE) {
  layer(data = data,
        mapping = mapping,
        stat = stat,
        geom = GeomSplitViolin,
        position = position,
        show.legend = show.legend,
        inherit.aes = inherit.aes,
        params = list(trim = trim,
                      scale = scale,
```

```
                      draw_quantiles = draw_quantiles,
                      na.rm = na.rm,
                      ...))
}

####Violin plots per vocabulary----
violinLVoc = ggplot(small, aes(Time, LVoc, colour=Group))+
  scale_colour_manual(values=c("#00BFC4","#F8766D"))

violinLVoc2<-violinLVoc+
  geom_split_violin(aes(group = interaction(Group, Time)),
                    alpha=0.1,
                    size=1.1,
                    trim=FALSE) +

  xlab("Time Point") +
  ylab("Model Estimated Vocabulary Knowledge") +
  theme_bw() +
  geom_point(alpha = 0.4, size=0.6, fill=NA) +
  geom_jitter(width = 0.2, height = 0.2, size=0.6)

violinLVoc1 = violinLVoc2 + aes(group = factor(ID))

violinLVocPlot<- violinLVoc1 +
  geom_smooth(aes(group=Group),
              method="lm",
              size=1.5,
              alpha=0.3) +
  labs(title="Growth in Vocabulary Knowledge",
       subtitle="Model estimated growth in vocabulary
                 knowledge grouped by LD status",
       x = "Time Point",
       fill="Group")
violinLVocPlot

png("VocPlot_Violin_Color.png",
    width = 8.5,
    height = 5.5,
    units = 'in',
    res = 300)
violinLVocPlot # Make plot
dev.off()

####Violin plots per reading comp----

violinRC = ggplot(small,
                  aes(Time, LRC, colour=Group))+
  scale_colour_manual(values=c("#00BFC4","#F8766D"))

violinRC2<- violinRC +
```

```
  geom_split_violin(aes(group = interaction(Group, Time)),
                    alpha=0.1,
                    size=1.1,
                    trim=FALSE) +
  xlab("Time Point") +
  ylab("Model Estimated Reading Comprehension") +
  theme_bw() +
  geom_point(alpha = 0.4,
             size=0.6,
             fill=NA) +
  geom_jitter(width = 0.2,
              height = 0.2,
              size=0.6)

violinRC1 = violinRC2 + aes(group = factor(ID))

violinRCPlot<- violinRC1 +
  geom_smooth(aes(group=factor(Group)),
              method="lm",
              size=1.5,
              alpha=0.3) +
  labs(title="Growth in Reading Comprehension",
       subtitle="Model estimated growth in reading comprehension grouped by L
D status",
       x = "Time Point",
       fill="Group")
violinRCPlot

png("RCPlot_Violin_Color.png",
    width = 8.5,
    height = 5.5,
    units = 'in',
    res = 300)
violinRCPlot # Make plot
dev.off()

####spaghetti plots per reading comp AND VOCAB----
spagRCVoc = ggplot(small, aes(LVoc, LRC, colour=Group)) +
  aes(group = factor(ID)) +
  geom_jitter() +
  ylab("Model Estimated Reading Comprehension") +
  xlab("Model Estimated Vocabulary Knowledge") +
  theme_bw() +
  scale_x_continuous(breaks=c(-3,-2,-1,0,1,2,3)) +
  scale_y_continuous(breaks=c(-3,-2,-1,0,1,2,3)) +
  scale_colour_manual(values=c("#00BFC4","#F8766D"))

spagRCVocSpaghetti= spagRCVoc +
  geom_path(aes(group=ID),
            arrow=arrow(length=unit(0.35,"cm")))
```

```
spagRCVocSpaghetti

png("RCVocSpaghetti_Color.png",
    width = 8.5,
    height = 5,
    units = 'in',
    res = 300)
spagRCVocSpaghetti # Make plot
dev.off()

#####making true vector plot plus confidence ellipses----
#### make new subset of data ----

dat$ID <- 1:nrow(dat)
set.seed(38)
ld_subset <- dat %>%
  filter (ESE7 == "1")
ld_IDs <- unique(ld_subset$ID)
sampled_IDs <- sample(ld_IDs, 100)
LDselect<-dat %>%
  filter (ID %in% sampled_IDs)

no_subset <- dat %>%
  filter (ESE7 == "0")
no_IDs <- unique(no_subset$ID)
nosampled_IDs <- sample(no_IDs, 100)
noselect<-dat %>%
  filter (ID %in% nosampled_IDs)

smallvec<- rbind(noselect, LDselect)



####for LD students----

#Creating matrix of model implied bivariate pairs
dimlength<-5
t1rcold<-seq(from = -2.5,to=1.5,
             length.out = dimlength)
t1vocld<-seq(from = -2.5,to=1,
             length.out = dimlength)
scorevecmut<-data.frame(rep(t1rcold,
                            times=dimlength))
scorevecmut$vocld<-rep(t1vocld,
                       each=dimlength)
colnames(scorevecmut)[1:2]<-c('t1rcold','t1vocld')

#Computing model implied scores at T2
scorevecmut$t2vocld<-
  scorevecmut$t1vocld+
```

```
  0.69+
  (-0.11*scorevecmut$t1vocld)+
  (0*scorevecmut$t1rcold)

scorevecmut$t2rcold<-
  scorevecmut$t1rcold+
  0.65+
  (-0.38*scorevecmut$t1rcold)+
  (0*scorevecmut$t1vocld)

####for non-ld students----

dimlength<-5
t1rco<-seq(from = -2.5,to=1.5,
           length.out = dimlength)
t1voc<-seq(from = -2.5,to=1,
           length.out = dimlength)
scorevecmut$rc<-rep(t1rco,
                    times=dimlength)
scorevecmut$voc<-rep(t1voc,
                     each=dimlength)
colnames(scorevecmut)[9:10]<-c('t1rco','t1voc')

#Computing model implied scores at T2
scorevecmut$t2voc<-
  scorevecmut$t1voc+
  0.89+
  (-0.03*scorevecmut$t1voc)+
  (-0.11*scorevecmut$t1rco)

scorevecmut$t2rco<-
  scorevecmut$t1rco+
  1.05+
  (-0.63*scorevecmut$t1rco)+
  (0.20*scorevecmut$t1voc)

####Plotting vector field----
g<-ggplot(smallvec,
          aes(PPVT3,
              SAT4),
          colour=factor(ESE7),
          show.legend=FALSE)+
  geom_jitter(alpha=.7,
              size=3,
              aes(colour=factor(ESE7)),
              show.legend=FALSE)+
  geom_segment(aes(x=t1voc,
                   y=t1rco,
                   xend=t2voc,
                   yend=t2rco),
```

```
               size=.8,
               arrow = arrow(length = unit(0.2,"cm")),
               data=scorevecmut,
               colour="#F8766D",
               show.legend=FALSE)+
  geom_segment(aes(x=t1vocld,
                   y=t1rcold,
                   xend=t2vocld,
                   yend=t2rcold),
               size=.8,
               arrow = arrow(length = unit(0.2,"cm")),
               data=scorevecmut,
               colour="#00BFC4",
               show.legend=FALSE)+
  xlab('Vocabulary Knowledge')+
  ylab('Reading Comprehension')+
  coord_cartesian(ylim = c(-2.8,1.9),
                  xlim=c(-2.8,1.9))+
  theme_bw(base_size = 19)+
  theme(panel.grid.minor = element_blank())+
  ylim(-3,3)+
  stat_ellipse(aes(colour=factor(ESE7)),
               lty=2,
               show.legend=FALSE,
               level = 0.90,
               size=1.1)
g

##Plot Save options----

#PNG high res
png("VocRC_Vector_Color.png",
    width = 11.5,
    height = 7.5,
    units = 'in',
    res = 600)
g # Make plot
dev.off()
```

Online Supplemental Materials IV

PPVT Scores Grouped by LD Status and FRL Status

Table S4.

PPVT Scores Grouped by LD Status and by FRL Status

	PPVT Scale Scores				Group Comparison		
FRL Status	*n*	No LD mean	*n*	LD mean	*t-test*	*p-value*	*comparison*
Did Not Apply	2463	103.48	76	97.01	4.28	< .001	No LD > LD
Denied	405	100.45	9	95.56	1.41	.197	No LD = LD
Reduced	1053	98.44	43	91.14	3.75	< .001	No LD > LD
Free	4932	92.71	245	85.71	8.16	< .001	No LD > LD
USDA Prov. 2	607	88.35	28	80.11	2.62	.014	No LD > LD

Note. Did not apply = Did not submit an application for FRL; Denied = denied eligibility for FRL; Reduced = Eligible for reduced price lunch; Free = Eligible for free lunch; USDA Prov. 2 = attended a USDA-approved Provision 2 designated school and received free meals.

Online Supplemental Materials V

Cross-Tabulations of Students with School-identified LD and students identified as low achieving through researcher-based cut-off criteria

The following tables include cross-tabulations of students with a school-identified LD and students identified as having low achievement in reading comprehension at the 5^{th}, 10^{th}, or 20^{th} percentiles in SAT-9/10 Reading Comprehension outcomes.

SLD versus Grade 1 Researcher-based criteria for SAT-9

The following tables show the cross-tabulations for students who were below the 5^{th}, 10^{th}, or 20^{th} percentile in SAT-9 in grade 1 compared to students who had a school-identified LD.

Table S5a.

School-identified LD versus 5^{th} Percentile in SAT-9 Reading Comprehension in Grade 1

		5th Percentile of SAT-9 in Grade 1		
		No	Yes	Total
School-identified LD	No	13569	577	14146
	Yes	415	***212***	627
κ = .265	Total	13984	789	14773

Table S5b.

School-identified LD versus 10^{th} Percentile in SAT-9 Reading Comprehension in Grade 1

		10th Percentile of SAT-9 in Grade 1		
		No	Yes	Total
School-identified LD	No	12994	1152	14146
	Yes	333	***294***	627
κ = .239	Total	13327	1446	14773

Table S5c.

School-identified LD versus 20th Percentile in SAT-9 Reading Comprehension in Grade 1

		20th Percentile of SAT-9 in Grade 1		
		No	Yes	Total
School-identified LD	No	12046	2100	14146
	Yes	263	***364***	627
κ = .180	Total	12309	2464	14773

SLD versus Grade 4 Researcher-based criteria for SAT-10

The following tables show the cross-tabulations for students who are below the 5th, 10th, or 20th percentile in SAT-10 in grade 4. These tables represent students who were in the lowest part of the distribution in fourth grade compared to students who have a school-identified LD.

Table S5d.

School-identified LD versus 5th Percentile in SAT-10 Reading Comprehension in Grade 4

		5th Percentile of SAT-10 in Grade 4		
		No	Yes	Total
School-identified LD	No	13623	523	14146
	Yes	414	***213***	627
κ = .280	Total	14037	736	14773

Table S5e.

School-identified LD versus 10th Percentile in SAT-10 Reading Comprehension in Grade 4

		10th Percentile of SAT-10 in Grade 4		
		No	Yes	Total
School-identified LD	No	12855	1291	14146
	Yes	342	***285***	627
κ = .211	Total	13197	1576	14773

Table S5f.

School-identified LD versus 20th Percentile in SAT-10 Reading Comprehension in Grade 4

		20th Percentile of SAT-10 in Grade 4		
		No	Yes	Total
School-identified LD	No	11623	2523	14146
	Yes	261	***366***	627
κ = .149	Total	11884	2889	14773

SLD versus students who met research-based criteria in both Grade 1 and Grade 4

The following tables show the cross-tabulations for students who are below the 5th, 10th, or 20th percentile in SAT-9/10 in both grade 1 and grade 4. These represent students who stay in the lowest part of the distribution over these four years compared to students who have a school-identified LD.

Table S5g.

School-identified LD versus students below the 5th percentile at both grades on SAT-9/10

		Below 5th percentile at both grades		
		No	Yes	Total
School-identified LD	No	14058	88	14146
	Yes	516	***111***	627
κ = .253	Total	14574	199	14773

Table S5h.

School-identified LD versus students below the 10th percentile at both grades on SAT-9/10

		Below 10th percentile at both grades		
		No	Yes	Total
School-identified LD	No	13842	304	14146
	Yes	457	***170***	627
κ = .283	Total	14299	474	14773

Table S5i.

School-identified LD versus students below the 20th percentile at both grades on SAT-9/10

		Below 20th percentile at both grades		
		No	Yes	Total
School-identified LD	No	13351	795	14146
	Yes	387	***240***	627
κ = .249	Total	13738	1035	14773

SLD versus students who improved their reading

The following table shows the cross-tabulations for students who were below the 20th percentile in SAT-9 in grade 1, but who improved to be above the 20th percentile in grade 4. This table represents the students who improved their reading to be above the typical reading low-achievement definition of the 20th percentile seen in reading research compared to students who had a school-identified LD.

Table S5j.

School-identified LD versus students who were below the 20th percentile in Grade 1 but above the 20th percentile in Grade 4

		Below 20th percentile in Grade 1; improved to above 20th in Grade 4		
		No	Yes	Total
School-identified LD	No	12841	1305	14146
	Yes	503	***124***	627
κ = .041	Total	13344	1429	14773

SLD versus late-emerging low achievers in reading

The following table show the cross-tabulations for students who did not meet low-achievement criteria in grade 1, but who met the definition for low-achievement in reading by being below the 20th percentile on SAT-10 in Grade 4. This table represents the students who had late-emerging low achievement in reading as those with normal reading in grade 1 who regressed below the 20th percentile in SAT-10 by fourth grade.

Table S5k.

School-identified LD versus students who were above the 20th percentile in Grade 1 but regressed below the 20th percentile in Grade 4

		No problem Grade 1; Below 20th in Grade 4		
		No	Yes	Total
School-identified LD	No	12418	1728	14146
	Yes	501	***126***	627
κ = .065	Total	12919	1854	14773

Online Supplemental Materials VI

Sample Statistics for Students below 20th percentile, Students with a school-identified LD, and students who were both SLD and below 20th percentile

	Below 20th Percentile			SLD Only			SLD & Below 20th Percentile		
	n	mean	SD	*n*	mean	SD	*n*	mean	SD
SAT - G1	331	500.53	18.99	375	517.54	36.39	137	485.76	22.01
SAT - G2	331	552.58	20.58	266	571.04	37.70	137	534.42	20.96
SAT - G3	331	577.85	18.63	470	598.43	38.60	137	561.60	19.88
SAT - G4	331	598.24	20.71	462	619.49	37.70	137	580.74	22.15
PPVT - K	315	67.72	14.74	269	79.46	16.82	132	73.28	17.38
PPVT - G1	320	81.75	14.85	256	94.40	17.90	132	87.26	18.14
PPVT - G2	328	94.67	15.42	271	105.39	18.70	134	98.58	17.52
PPVT - G3	283	108.30	16.84	215	117.57	18.01	91	110.10	19.31

Note. Sample sizes fluctuate due to missing data. SLD = school-identified LD students; SAT = Stanford achievement test; PPVT = Peabody Picture Vocabulary Test.

Non-SLD Students who were below the 20th percentile started with higher SAT scores and maintained higher SAT scores than students who were SLD only or who were both SLD and also below the 20th percentile. Students who were SLD had higher vocabulary scores compared to non-SLD students below the 20th percentile and compared to SLD students who were persistently poor readers. Non-SLD students who were below the 20th percentile on SAT had the lowest vocabulary scores and maintained lower vocabulary scores across K-3rd grade.

Online Supplemental Materials VII

Model Comparison between Students with a School-Identified LD and Students persistently below the 20th percentile in SAT-9/10

A group of readers who were persistently below the 20th percentile at all four SAT-9/10 measurements was selected for a model comparison to students with a school-identified LD. A subsample of 331 students were selected who scored below the 20th percentile on SAT-9/10 in all of first through fourth grades. These students were compared to the model of students with an LD (n = 627).

As was done for the models within the manuscript, the model for students below the 20th percentile was fit separately from the model for students with an LD to determine the cross-lagged relations between vocabulary knowledge and reading comprehension. Four models were fit to this data: 1) a bidirectional coupling model, where vocabulary predicted change in reading comprehension and reading comprehension predicted change in vocabulary; 2) a unidirectional model where vocabulary predicted change in reading comprehension, but not vice versa; 3) a second unidirectional model, whereby reading comprehension predicted change in vocabulary but not vice versa, and 4) a no-coupling model, where all of the cross-lagged pathways were set to zero.

Results of the model comparison for persistently poor readers below the 20th percentile showed that although the bidirectional and two unidirectional models fit well, they fit equally as well as a model fixing all cross-lagged pathways to zero (χ^2 [25] = 40.17, p = .015; CFI = .98; TLI = .97; RMSEA = .043 [90% C.I. .014 - .066]). Parameter estimates from this model are presented in Table S7b.

Students persistently below the 20th percentile started Kindergarten ($\mu_v = -1.57$) half a standard deviation below the mean of students who were school-identified as having an LD ($\mu_v = -1.07$). Both groups of students started low in reading comprehension ($\mu_r = -1.39;\ -1.24$), but the linear slope for students with an LD was slightly larger (η_r = 0.65) than persistently poor readers (η_r = 0.52). The auto-regressive parameter for persistently poor readers was not significantly different from zero (*p* = .806). The cross-lagged pathways were fixed to zero for model parsimony. For reference, the cross-lagged pathway from vocabulary to change in reading comprehension (γ_{rcv} = .16, *se* = .21, *p* = .450), and the cross-lagged pathway from reading comprehension to change in vocabulary knowledge (γ_{vrc} = 0.06, *se* = .05, *p* = .245) were not significant in the bidirectional model for persistently poor readers.

In summary, these 331 students who were persistently poor readers not only started First Grade slightly lower in reading comprehension, but also started Kindergarten with lower vocabulary knowledge than their peers who had school-identified LD. These persistently poor readers represent a different subsample of the Title-I sample of students, as these are students who were not identified by their teachers or caregivers as having a learning disability.

Table S7a.

Model fit statistics for the Bivariate Latent Change Score Models

Model	χ^2	*df*	*SCR*	RMSEA	90% CI	CFI	TLI	SRMR	nBIC
Persistently poor readers below the 20th percentile in SAT-9/10									
Model S7a	40.02	23	1.12	.047	.021 - .071	.97	.97	.06	3999.25
Model S7b	42.39	24	1.09	.048	.023 - .071	.97	.97	.06	3997.90
Model S7c	39.18	24	1.18	.044	.015 - .068	.98	.97	.05	3997.96
Model S7d	**40.17**	**25**	**1.17**	**.043**	**.014 - .066**	**.98**	**.97**	**.05**	**3996.06**
LD Students (same single-group models as the manuscript)									
Model 2A	49.60	22	1.13	.045	.028 - .061	.98	.97	.04	7682.38
Model 2B	46.56	23	1.22	.040	.023 - .057	.99	.98	.04	7680.12
Model 2C	51.62	23	1.10	.045	.028 - .061	.98	.98	.04	7679.92
Model 2D	**47.27**	**24**	**1.21**	**.039**	**.022 - .056**	**.99**	**.98**	**.04**	**7677.31**

Note. χ2 = Chi-Square test of model fit; df = degrees of freedom. SCR = scaling correction factor for Satorra-Bentler chi-square difference testing; RMSEA = Root Mean-Squared Error of Approximation. CI = Confidence interval. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. SRMR = standardized root mean square residual; nBIC = Sample size adjusted Bayesian information criteria.

Table S7b.

Parameters for the supplemental multiple group LCS model

	Below 20th %-ile *n = 331*		With an LD *n = 627*	
Parameter	*Vocab*	*RC*	*Vocab*	*RC*
Initial mean status, $\mu_{intercept}$	-1.57***	-1.39***	-1.07***	-1.24***
Linear slope, η_{slope}	0.78***	0.52***	0.69***	0.65***
Auto-Regression, β	0.01^{ns}	-0.42***	-0.11**	-0.38***
Cross-lagged effects, γ:				
RC → Δ Vocab	0		0	
Vocab → Δ RC	0		0	
Variances:				
Intercepts, σ_0^2	0.49***	0.07***	0.78***	0.40***
Slopes, σ_s^2	0.02*	0.02***	0.04***	0.11***
Residual Errors, σ_e^2	0.24***	0.12***	0.25***	0.21***
Covariances:				
Vocab $\mu_{intercept}$ ↔ Vocab μ_{slope}	$-.12^{ns}$		.39*	
Vocab $\mu_{intercept}$ ↔ RC $\mu_{intercept}$	$-.04^{ns}$		.34***	
Vocab $\mu_{intercept}$ ↔ RC μ_{slope}	$-.09^{ns}$		.32***	
RC $\mu_{intercept}$ ↔ RC μ_{slope}	.60***		.53***	
RC $\mu_{intercept}$ ↔ Vocab μ_{slope}	$.33^{*}$		.19*	
Vocab μ_{slope} ↔ RC μ_{slope}	$.27^{ns}$		.52***	

Note. Vocab= PPVT vocabulary; RC = SAT reading comprehension. ^{ns} = not significant, *** = $p < .001$; ** = $p < .01$; * = $p < .05$. Residual variances were fixed across groups; all other parameters were freely estimated across groups.