Modeling the Impact of Virtual Learning on Relative Student Performance

Technical Report

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Overview

The COVID-19 pandemic prompted the Knox County School system (KCS) to offer virtual learning and in-person programming during the 2020-2021 academic year (SY2021). KCS families chose to enroll their students in whichever learning modality best suited their circumstances and preferences. The REA department previously published investigations into the observable differences between students in virtual and in-person programs (Sattler, 2021c; Sattler, 2021d), perception data related to the virtual program (Sattler, 2021b), and impact on student grades (Sattler 2021a).

The finalization of standardized state-level testing allows KCS to estimate the impact virtual learning had on students' SY2021 test scores. The results of this study may be useful in determining the extent of student learning losses from instructional shifts, shaping policy for the KCS virtual school launched at the start of SY2122, and provide a benchmark from which to monitor the effectiveness of the KCS virtual schools.

The REA department explored the impact of virtual instruction on student test scores using two methodologies: hierarchical linear modeling (HLM) and structural equation modeling (SEM). The results of those explorations are contained in this technical report. Readers of this report should note that state testing data was not available from SY1920 because of pandemic-related school closures.

Methodology

Students could be enrolled in four different learning environments during SY2021. KCS allowed students to initially opt into the virtual program during summer 2021 (July 15 through July 22). A transfer window ran from October 26 to November 6 to allow movement between virtual and in-person instruction. REA staff exported program enrollment data four times (the beginning of the first semester, the end of the first semester, the beginning of the second semester, and the end of the second semester). The researcher classified students into three categories based on the percentage SY2021 spent in a virtual environment.

- Virtual = 0%: Students were considered in-person learners if enrolled in a traditional classroom setting in each export.
- Virtual = 100%: Students were considered virtual learners if enrolled in the virtual program in each export.
- Virtual = 25%, 50%, or 75%: Students were considered a mixed enrollee if enrolled in a mixture of in-person and virtual settings during SY2021. Virtual enrollment was calculated as the percentage of exports in which the student was enrolled as a virtual learner.

Virtual learners were enrolled in a variety of virtual learning environments. Some students received virtual instruction from a teacher based in their zoned school. Other students received virtual instruction from a teacher hired to teach within the district's Quality Education for Students Using Technology program (QuEST). A small number of students were instructed through a third-party contractor (the Florida Virtual School).

Students experienced further variation in their virtual learning environment due to their grade band. Virtual elementary students learned in largely synchronous environments in state-tested subjects (Reading/Language Arts, Math, and Science). Virtual secondary students mostly learned in asynchronous environments and they could enroll in a mixture of zoned-school, QuEST, and FLVS virtual courses.

This study estimates the impact of any virtual learning paradigm on state tests. Differences between virtual learning environments were ignored due to the fluid nature of virtual enrollment, especially among secondary students. The researcher used the change in students' state normal curve equivalents (NCEs, between SY1819 and SY2021) as the outcome of interest. Scaled scores and performance categories were not used because the state department of education does not create scales and cut-points aligned across grade levels. Students' state percentiles from SY1819 were linked to SY2021 percentiles through students' state identification numbers. Demographics data came from SY2021 end-of-the-year student demographics.

Methodology: Hierarchical Linear Modeling with Treatment/Control Matching

This analysis compared changes in NCEs between 0% virtual students (the control group) and 100% virtual students (the treatment group). Data were analyzed by content area. Math subjects included grades 5-8 math, Algebra I, Geometry, Algebra II, Integrated Math I, Integrated Math II, and Integrated Math III. English/Language Arts (ELA) subjects included grades 3-8 ELA, English I, and English II.

Coarsened exact matching (CEM) was used to create the treatment and control groups. CEM used the MatchIt package (version 4.0.0) for R software. Exact matching was required on the following demographic variables: school in which the student tested in SY2021, race/ethnicity, gender, economically disadvantaged status, special education status, English language learner status, and a dichotomous indicator (1, 0) to indicate if a student changed schools between the end of SY1819 and the end of SY2021. Withdraw data from the KCS student information system (ASPEN) identified students who moved between schools before the end of SY2021. Additionally, students were matched on their SY1819 content-specific NCE using MatchIt's automatic coarsening algorithm. K-to-K matching was used to ensure balanced sample sizes between treatment and control groups.

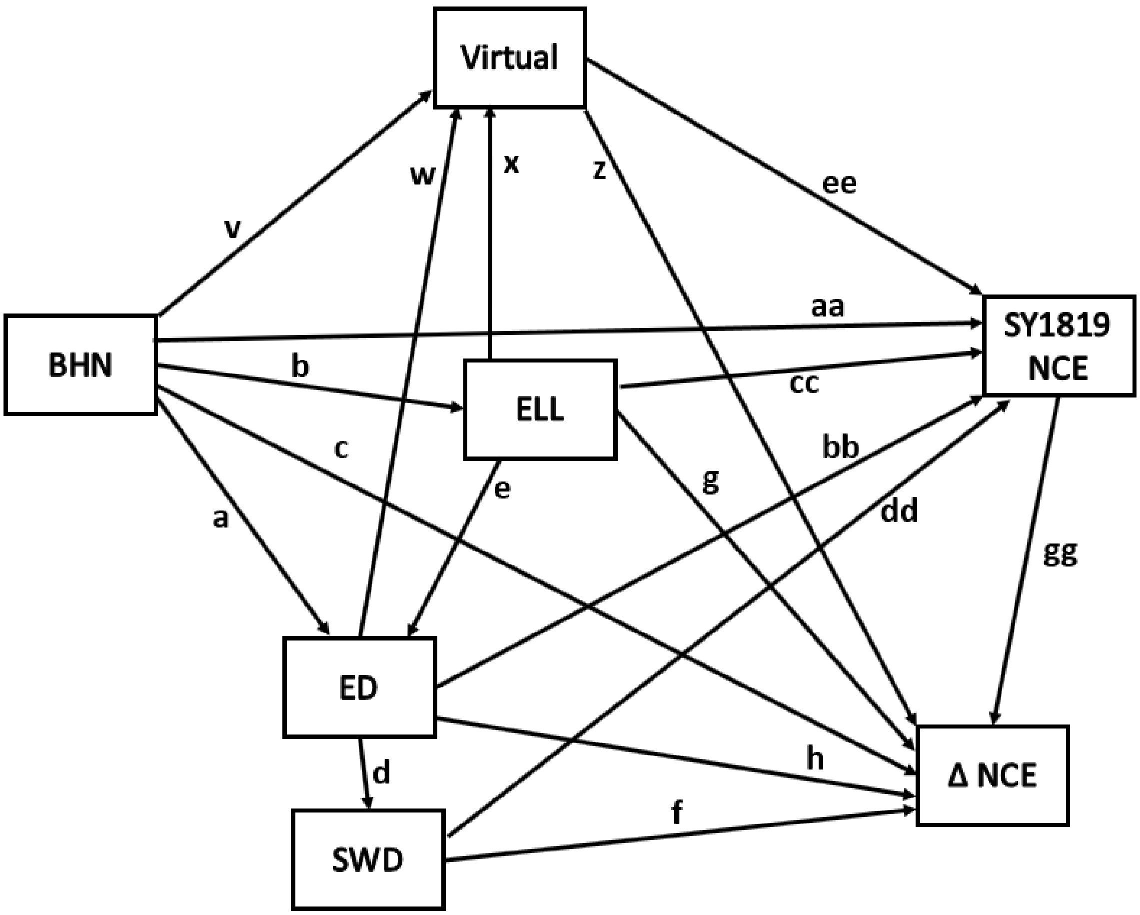
Hierarchical Linear Modeling was used to estimate the treatment effect on the mean change in NCE. The dependent variable was the students' change in NCE, and the independent variables were the students' SY1819 NCE and the school in which they tested in SY2021.

$$Change\ in\ NCE_{ij} = \gamma_{00} + \beta_0 * SY1819\ NCE_{ij} + \beta_1 * Virtual_{ij} + \mu_{oj} + r_{ij}$$

The SY1819 NCE was included as a dependent variable because of floor and ceiling effects. A random intercept term (μ_{oj}) was included to compare the estimated treatment effect (β_1) with the estimated school-level effects. HLM used the lme4 package (version 1.1-27.1) for R software. The modeling used maximum likelihood criteria.

Methodology: Structural Equation Modeling

This analysis used SEM to compare changes in NCE among 0%, 25%, 50%, 75%, and 100% virtual students. Data was analyzed by content area (as above). The path model was modified from previous REA research estimating the impact of demographics on state test data (Sattler, 2019) and has basis in peer-reviewed research (Page, 1981; Blair, 2002; Kieffer, 2010). The path model used in the analysis is contained in Figure 1. Intercept terms have been removed from Figure 1 for clarity.



Paths v, w, x, and ee were included because of the variations observed in virtual learning enrollment during the first semester of SY2021 (Sattler, 2021c). The direct impact of virtual instruction on the change in NCE is quantified through path z.

School effects could not be included in the SEM due to the number of schools that would need to be included (82). The population used in the SEM included students who were enrolled in the same school in SY1819 and SY2021 to minimize school effect bias on the path coefficients. Students matriculating across grade bands before the end of SY2021 were excluded from the study. This methodology limited the research population to students who were enrolled in grades 5, 7, and 11 in SY2021. All NCE values were divided by 100 to keep the scale of the variables consistent.

SEM analysis used the lavaan package (version 0.6-9) for R software.

Results: Hierarchical Linear Modeling with Treatment/Control Matching, Math

There were 16,520 students in the non-matched control group and 4,635 in the treatment group. The number of matched students in the treatment (virtual enrollment = 100%) and control groups (virtual enrollment = 0%) was 2,387.

Table 1 compares the students in the HLM population compared to all students in the district. The HLM population included students who took the state test in Knox County in SY1819 and SY2021 that could be matched in a treatment-control pair. The "Virtual = 100%" population includes all students coded as virtual learners in each SY2021 period. The "Virtual = 0%" population included all students coded as in-person learners in each SY2021 period.

Table 1: Math Demographics

	HLM Treatment	HLM Control	Virtual = 100%	Virtual = 0%
N	2387	2387	10904	39141
Nat. Amer.	0.0%	0.0%	0.6%	0.3%
Asian	2.3%	2.3%	7.5%	2.0%
Afr. Am.	14.4%	14.4%	22.2%	13.9%
Hispanic/ Latino	6.4%	6.4%	9.7%	12.0%
Pac. Isldr.	0.0%	0.0%	0.2%	0.2%
White	76.9%	76.9%	59.9%	71.6%
Female	51.0%	51.0%	51.3%	47.5%
ED	19.6%	19.6%	29.8%	22.6%
SpEd	4.2%	4.2%	13.3%	15.1%
EL	0.5%	0.5%	2.9%	8.5%

The variables related to the HLM population are noticeably different in some demographics. Table 1 suggests the HLM results may not be generalizable to all Knox County students. A generalizable causal comparison of virtual and in-person results is impossible because the population who enrolled in virtual instruction was incomparable to the population who enrolled in in-person instruction.

Table 2 shows the mean SY1819 math NCE for the populations pertinent to this study. Table 2 suggests that the CEM provided a good match between treatment and control groups.

However, the data suggest that matches weren't found for lower-performing students who were virtual learners.

Table 2: SY1819 Math NCEs

Population	N	Mean SY1819 NCE	St. Dev. SY1819 NCE
Treatment Matched	2387	54.4	17.9
Control Matched	2387	54.4	17.9
Treatment Unmatched	2248	47.7	23.2
Control Unmatched	14133	51.8	21.8
All Virtual = 100%	4635	51.2	20.9
All Virtual = 0%	16520	52.2	21.3

The fixed effects for the math HLM model are available in Table 3. The estimated impact of virtual learning was a mean loss of 5.3 math NCEs when compared to in-person learners (among the population of students who could be matched via CEM).

Table 3: Math HLM Fixed Effects

Fixed Effects	Estimate	Std. Error	t value
γ_{00}: Intercept (District-level)	16.6	0.9	19.3
β_0 (District-level)	-0.3	0.0	-22.5
β_1 (District-level)	-5.3	0.4	-14.7

The distribution of random effects is shown in Figure 2. Each point in Figure 2 represents the change in NCE associated with a KCS school. The horizontal lines show the 95% confidence intervals for the random effects. The red vertical line at x = -5.3 is the district level estimate for virtual instruction. Figure 2 demonstrates that the change in mean NCE among the virtual students was comparable to the KCS schools with the highest losses.

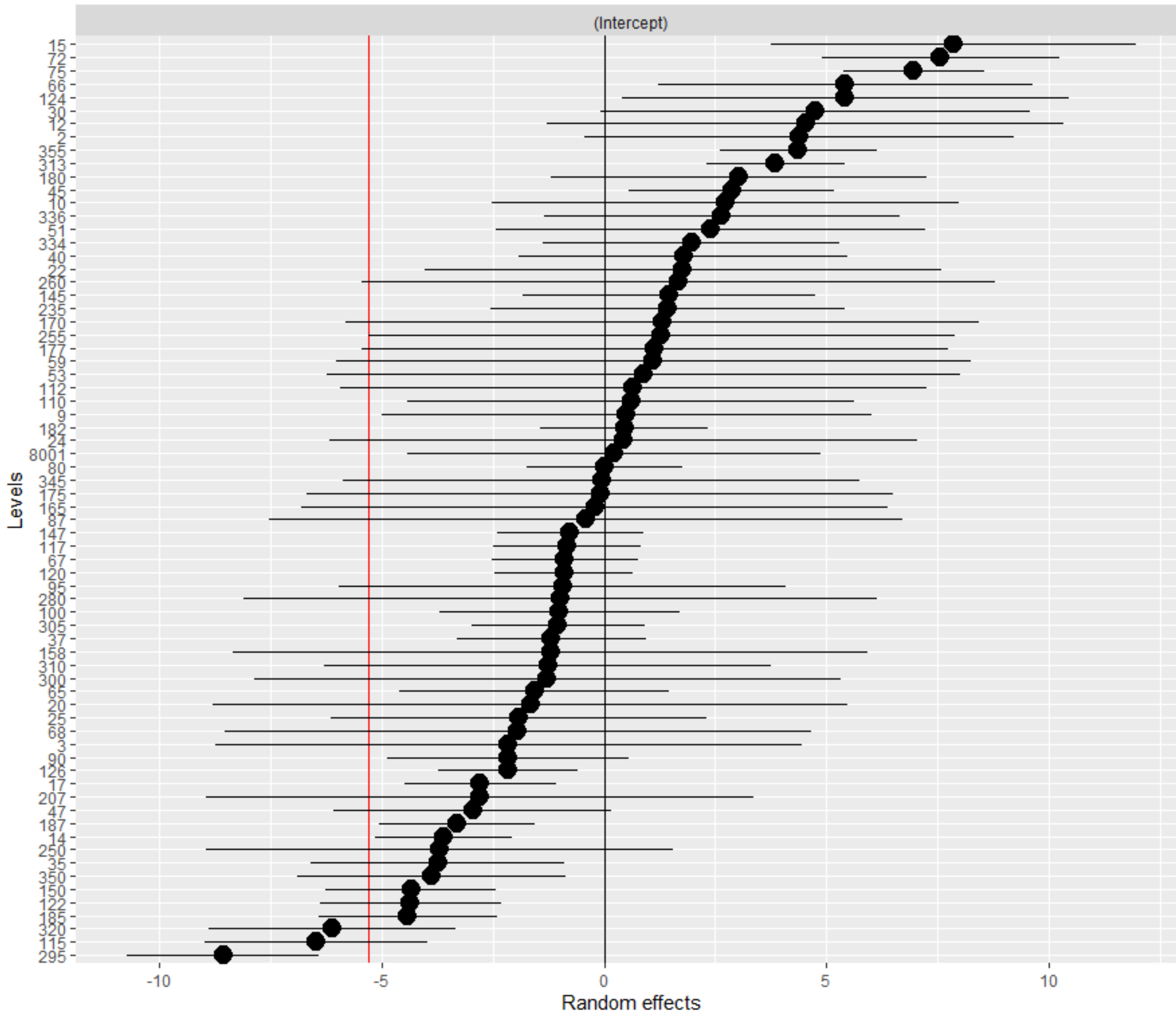


Figure 2: Math HLM Random Effects

Figure 3 shows the district-level relationship between SY1819 math NCE and change in NCE for treatment and control groups.

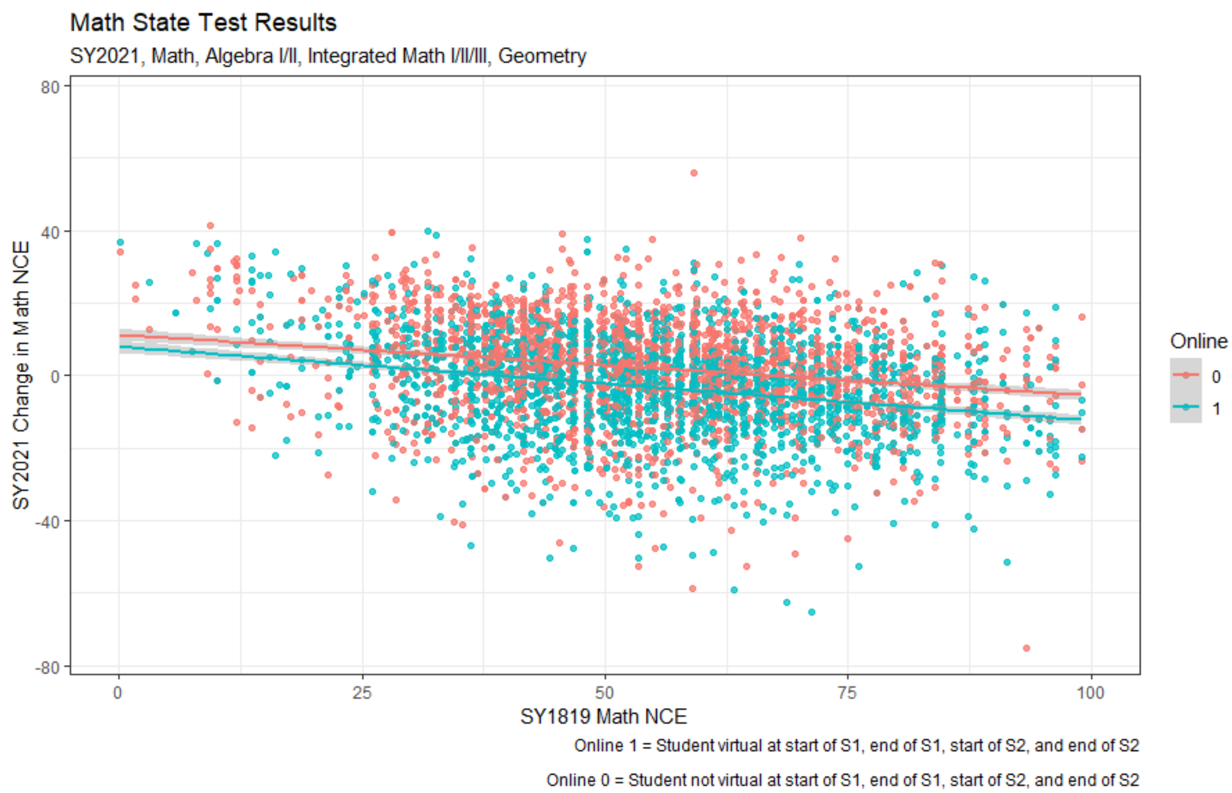


Figure 3: Math Change in NCE by SY1819 NCE

Results: Hierarchical Linear Modeling with Treatment/Control Matching, ELA

There were 13,301 students in the non-matched control group and 2,160 in the treatment group. The number of matched students in the treatment (virtual enrollment = 100%) and control groups (virtual enrollment = 0%) was 2,146.

Table 4 compares the students in the HLM population compared to all students in the district. The HLM population included students who took the state test in Knox County in SY1819 and SY2021 that could be matched in a treatment-control pair. The “Virtual = 100%” population includes all students coded as virtual learners in each period. The “Virtual = 0%” population included all students coded as in-person learners in each period.

Table 4: ELA Demographics

	HLM Treatment	HLM Control	Virtual = 100%	Virtual = 0%
N	2146	2146	10904	39141
Nat. Amer.	0.0%	0.0%	0.6%	0.3%
Asian	2.3%	2.3%	7.5%	2.0%
Afr. Am.	14.0%	14.0%	22.2%	13.9%
Hispanic/ Latino	6.5%	6.5%	9.7%	12.0%
Pac. Isldr.	0.0%	0.0%	0.2%	0.2%
White	77.2%	77.2%	59.9%	71.6%
Female	49.9%	49.9%	51.3%	47.5%
ED	19.5%	19.5%	29.8%	22.6%
SpEd	3.5%	3.5%	13.3%	15.1%
EL	0.3%	0.3%	2.9%	8.5%

The variables related to the HLM population are noticeably different in some demographics. Table 4 suggests the HLM results may not be generalizable to all Knox County students. A generalizable causal comparison of virtual and in-person results is impossible because the population who enrolled in virtual instruction was incomparable to the population who enrolled in in-person instruction.

Table 5 shows the mean SY1819 ELA NCE for the populations pertinent to this study. Table 5 suggests that the CEM provided a good match between treatment and control groups. However, the data suggest that matches weren't found for lower-performing students who were virtual learners.

Table 5: SY1819 ELA NCEs

Population	N	Mean SY1819 NCE	St. Dev. SY1819 NCE
Treatment Matched	2146	57.4	18.3
Control Matched	2146	57.3	18.3
Treatment Unmatched	2160	50.0	23.5
Control Unmatched	13301	53.2	22.5
All Virtual = 100%	4306	53.7	21.4
All Virtual = 0%	15447	53.8	22.0

The fixed effects for the ELA HLM model are available in Table 6. The estimated impact of virtual learning was a mean loss of 2.4 ELA NCEs when compared to in-person learners (among the population of students who could be matched via CEM).

Table 6: ELA HLM Fixed Effects

Fixed Effects	Estimate	Std. Error	t value
γ_{00}: Intercept (District-level)	15.4	0.9	18.0
β_0 (District-level)	-0.3	0.0	-21.8
β_1 (District-level)	-2.4	0.4	-6.1

The distribution of random effects is in Figure 4. Each point in Figure 4 represents the change in NCE associated with a KCS school. The horizontal lines show the 95% confidence intervals for the random effects. The red vertical line at x = -2.4 is the district level estimate for virtual instruction. Figure 4 demonstrates that the change in mean NCE among the virtual students was comparable to the KCS schools with the highest losses.

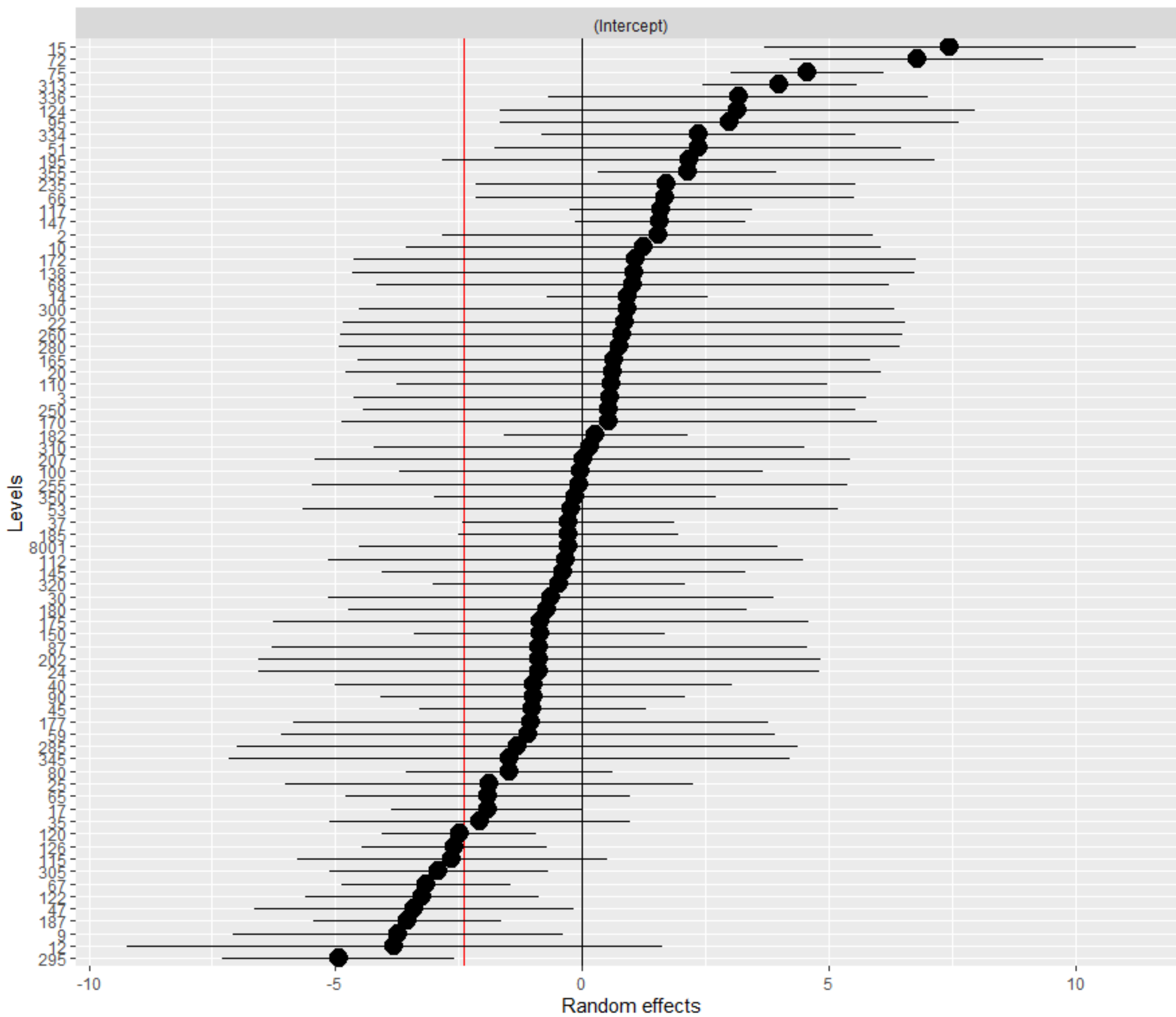


Figure 4 ELA HLM Random Effects

Figure 5 shows the district-level relationship between SY1819 ELA NCE and change in NCE for treatment and control groups.

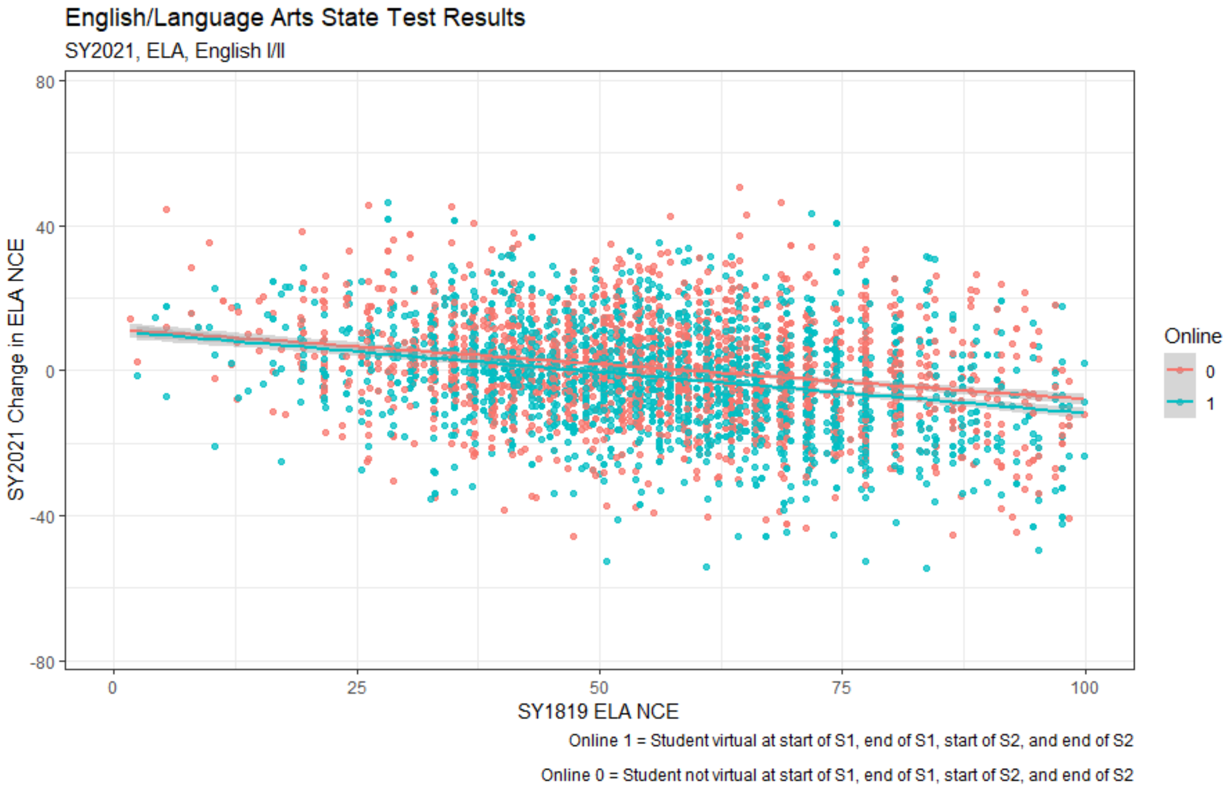


Figure 5: Math Change in NCE by SY1819 NCE

Results: Structural Equation Modeling, Math

The demographics of the students used in the math SEM analysis are in Table 7. Table 7 indicates there is considerable variation in student demographics across the virtual classification groups.

Table 7: Math SEM Demographics

	Virtual = 0%	Virtual = 25%	Virtual = 50%	Virtual = 75%	Virtual = 100%
N	5460	55	192	1082	1666
N EOC	1898	40	96	326	492
N TNReady	3562	15	96	756	1174
Nat. Amer.	0.3%	0.0%	0.5%	0.4%	0.4%
Asian	2.1%	3.6%	0.5%	1.9%	5.9%
Afr. Am.	12.7%	18.2%	18.8%	20.0%	21.8%
Hispanic/ Latino	10.9%	14.5%	13.0%	14.9%	11.5%
Pac. Isldr.	0.2%	0.0%	0.0%	0.4%	0.1%
White	73.9%	63.6%	67.2%	62.5%	60.2%
Female	45.9%	50.9%	55.7%	48.6%	49.9%
ED	19.1%	30.9%	32.3%	30.7%	26.8%
SpEd	12.9%	23.6%	10.4%	13.9%	10.9%
EL	3.8%	7.3%	2.1%	4.3%	2.2%

The variance/covariance matrix or the math data is contained in Table 8.

Table 8: Math Variance/Covariance Matrix

	BHN	ED	EL	SpEd	Virtual	SY1819 NCE	Δ NCE
BHN	0.199						
ED	0.056	0.174					
EL	0.022	0.004	0.034				
SpEd	0.004	0.015	0.004	0.110			
Virtual	0.020	0.018	-0.002	-0.002	0.181		
SY1819 NCE	-0.027	-0.025	-0.008	-0.026	-0.005	0.043	
Δ NCE	0.001	-0.001	0.002	0.005	-0.009	-0.011	0.021

The results of the path analysis indicate that the model in Figure 1 provides a good fit to the observed data (Hu, 1999). The Comparative Fit Index (CFI) is above the cut-off for an acceptable model (model CFI = 0.995, cut-off CFI = 0.90) and the Root Mean Square Error of Approximation (RMSEA) is below the cut-off for an acceptable fit (model RMSEA = 0.034, cut-off RMSE = 0.060). The parameter estimates for the paths are in Table 9. The SEM model estimates the direct effect of virtual instruction was a -5.4 change in math NCE.

Table 9: Math SEM Parameter Estimates

Parameter	Path	Estimate	Std. Error	z-value	P(>|z|)
Δ NCE~BHN	c	-0.020	0.004	-5.562	0.000
Δ NCE~EL	g	-0.012	0.008	-1.425	0.154
Δ NCE~ED	h	-0.035	0.004	-9.370	0.000
Δ NCE~SpEd	f	-0.018	0.005	-3.866	0.000
Δ NCE~Virtual	z	-0.054	0.003	-15.940	0.000
Δ NCE~SY1819 NCE	gg	-0.301	0.008	-37.678	0.000
ED~BHN	a	0.289	0.010	28.781	0.000
ED~EL	e	-0.077	0.024	-3.174	0.002
SpEd~ED	d	0.087	0.009	10.155	0.000
EL~BH	b	0.108	0.004	24.902	0.000
Virtual~ED	w	0.072	0.012	6.271	0.000
Virtual~BHN	v	0.096	0.011	8.642	0.000
Virtual~EL	x	-0.129	0.026	-5.021	0.000
SY1819 NCE~BHN	aa	-0.084	0.005	-17.749	0.000
SY1819 NCE~ED	bb	-0.091	0.005	-18.507	0.000
SY1819 NCE~EL	cc	-0.163	0.011	-14.944	0.000
SY1819 NCE~SpEd	dd	-0.217	0.006	-36.976	0.000
SY1819 NCE~Virtual	ee	-0.013	0.005	-2.766	0.006
Δ NCE Intercept		0.209	0.005	40.670	0.000
ED Intercept		0.148	0.005	29.144	0.000
SpEd Intercept		0.107	0.004	26.151	0.000
EL Intercept		0.006	0.002	2.503	0.012
Virtual Intercept		0.268	0.006	47.370	0.000
SY1819 NCE Intercept		0.590	0.003	213.931	0.000
BHN Intercept		0.275	0.005	56.612	0.000
Δ NCE Variance		0.017	0.000	65.019	0.000
ED Variance		0.158	0.002	65.019	0.000
SpEd Variance		0.109	0.002	65.019	0.000
EL Variance		0.032	0.000	65.019	0.000
Virtual Variance		0.178	0.003	65.019	0.000
SY1819 NCE Variance		0.032	0.000	65.019	0.000
BHN Variance		0.199	0.003	65.019	0.000

Results: Structural Equation Modeling, ELA

The demographics of the students used in the ELA SEM analysis are in Table 10. Table 10 indicates there is considerable variation in student demographics across the virtual classification groups. Table 10 also indicates that few high school students were included in the ELA analysis. The ELA sequence in high school typically involves English I in grade 9 and English II in grade 10. Most students who took English I in SY1819 took English II in SY1920 when there was no state testing. The students enrolled in English I during SY2021 are not included with their grade 7 test results because we constrained the population in this analysis to students who did not change schools between SY1819 and SY2021.

Table 10: ELA SEM Demographics

	Virtual = 0%	Virtual = 25%	Virtual = 50%	Virtual = 75%	Virtual = 100%
N	4267	23	107	857	1342
N EOC	33	0	4	9	7
N TNReady	4234	23	103	848	1335
Nat. Amer.	0.2%	0.0%	0.9%	0.5%	0.4%
Asian	2.2%	8.7%	1.9%	2.1%	6.4%
Afr. Am.	12.1%	17.4%	24.3%	21.2%	23.2%
Hispanic/ Latino	11.4%	8.7%	15.0%	15.1%	12.0%
Pac. Isldr.	0.3%	0.0%	0.0%	0.5%	0.1%
White	73.9%	65.2%	57.9%	60.7%	57.8%
Female	47.1%	47.8%	56.1%	47.0%	47.6%
ED	19.9%	47.8%	37.4%	32.2%	27.9%
SpEd	12.4%	21.7%	10.3%	13.4%	10.4%
EL	3.6%	8.7%	1.9%	4.9%	2.2%

The variance/covariance matrix or the ELA data is contained in Table 11.

Table 11: ELA Variance/Covariance Matrix

	BHN	ED	EL	SpEd	Virtual	SY1819 NCE	Δ NCE
BHN	0.202						
ED	0.061	0.180					
EL	0.021	0.005	0.034				
SpEd	0.007	0.018	0.005	0.106			
Virtual	0.025	0.019	-0.001	-0.002	0.185		
SY1819 NCE	-0.030	-0.029	-0.011	-0.030	-0.004	0.049	
Δ NCE	0.002	-0.001	0.002	0.003	-0.006	-0.011	0.021

The results of the path analysis indicate that the model in Figure 1 provides a good fit to the observed data (Hu, 1999). The Comparative Fit Index (CFI) is above the cut-off for an acceptable model (model CFI = 0.993, cut-off CFI = 0.90) and the Root Mean Square Error of Approximation (RMSEA) is below the cut-off for an acceptable fit (model RMSEA = 0.042, cut-off RMSE = 0.060). The parameter estimates for the paths are in Table 12. The SEM model estimates the direct effect of virtual instruction was a -3.1 change in ELA NCE.

Table 12: ELA SEM Parameter Estimates

Parameter	Path	Estimate	Std. Error	z-value	P(>|z|)
Δ NCE~BHN	c	-0.015	0.004	-3.616	0.000
Δ NCE~EL	g	-0.020	0.009	-2.131	0.033
Δ NCE~ED	h	-0.037	0.004	-8.925	0.000
Δ NCE~SpEd	f	-0.042	0.006	-7.687	0.000
Δ NCE~Virtual	z	-0.031	0.004	-8.138	0.000
Δ NCE~SY1819 NCE	gg	-0.280	0.009	-31.420	0.000
ED~BHN	a	0.308	0.011	27.071	0.000
ED~EL	e	-0.054	0.028	-1.952	0.051
SpEd~ED	d	0.097	0.009	10.381	0.000
EL~BH	b	0.102	0.005	21.049	0.000
Virtual~ED	w	0.068	0.013	5.220	0.000
Virtual~BHN	v	0.115	0.013	9.033	0.000
Virtual~EL	x	-0.121	0.029	-4.117	0.000
SY1819 NCE~BHN	aa	-0.085	0.005	-15.476	0.000
SY1819 NCE~ED	bb	-0.100	0.006	-17.584	0.000
SY1819 NCE~EL	cc	-0.238	0.013	-18.685	0.000
SY1819 NCE~SpEd	dd	-0.251	0.007	-35.935	0.000
SY1819 NCE~Virtual	ee	-0.004	0.005	-0.727	0.467
Δ NCE Intercept		0.185	0.006	30.388	0.000
ED Intercept		0.151	0.006	25.820	0.000
SpEd Intercept		0.098	0.005	21.512	0.000
EL Intercept		0.006	0.003	2.371	0.018
Virtual Intercept		0.266	0.006	41.074	0.000
SY1819 NCE Intercept		0.632	0.003	197.561	0.000
BHN Intercept		0.281	0.006	50.744	0.000
Δ NCE Variance		0.018	0.000	57.428	0.000
ED Variance		0.161	0.003	57.428	0.000
SpEd Variance		0.105	0.002	57.428	0.000
EL Variance		0.032	0.001	57.428	0.000
Virtual Variance		0.181	0.003	57.428	0.000
SY1819 NCE Variance		0.034	0.001	57.428	0.000
BHN Variance		0.202	0.004	57.428	0.000

Conclusions & Considerations

The analysis suggests that students who opted for virtual instruction in SY2021 were more likely to lose pace with their in-person peers. The results further suggest that losses were greater in math (approximately 5 NCEs lost) when compared to English Language Arts (between 2 and 3 NCEs lost). The findings seem reasonable in magnitude, as the losses are comparable to the most negative estimated school effects. The difference between the estimated losses in ELA and Math also seems plausible, as our findings parallel those of other research about COVID-19 related losses (Curriculum Associates, 2020; Lewis, 2021).

The majority of SY2021 virtual students returned to in-person learning in SY2122. This may present unique challenges, as these findings suggest within-school student performance will be greater than in the past. District investments in formative assessment tools should help identify lingering performance gaps and monitor the effectiveness of instructional strategies in closing gaps.

Negative effects on student outcomes may not be unexpected as KCS teachers and students were adjusting to new learning modalities. However, the continued negative performance of KCS virtual learners may signal that the district should provide more robust student supports for virtual instruction.

The findings from this study can also help set goals for the KCS virtual schools. District policymakers can compare Tennessee Value-Added Assessment System (TVAAS) growth estimates to the estimates calculated in this study. Such comparisons can provide evidence that KCS virtual instruction is improving.

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