Estimating the Impact of Online Instruction on Grade Point Averages Among the 2020-2021 Senior Cohort

Technical Report

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Overview

The onset of the COVID-19 pandemic prompted the Knox County School system (KCS) to offer alternative instructional delivery modes during the 2020-2021 school year (SY2021). Approximately 30% of the students enrolled in KCS opted to receive online instruction during the first semester of SY2021. The department of Research, Evaluation, and Assessment (REA) has produced interim reports related to the distributions of course grades throughout the first semester of SY2021. These distributions indicate the number of failing grades dramatically increased during the first quarters of SY2021.

This study was conducted by REA to better understand how changes in grades correlate to student characteristics and specific learning modalities. Hierarchical regression analysis was used to monitor changes in grade point averages (GPAs) among the SY2021 senior cohort. The findings from this study may inform district policy related to online instruction and refine future research questions related to online learning outcomes.

Findings suggest the impact of online instruction on student GPAs is complex and entangled with interactions among demographic variables. Although our analysis suggests that students who opted for online learning during the first semester of SY2021 were more likely to experience decreases in GPAs, data suggest that there are relatively large proportions of students whose GPAs have been unaffected by leaving the traditional in-person classroom.

Methodology

Student grades are multi-faceted variables that can be influenced by variation in teacher-level expectations, school-level policy, and course content. The grade point average (GPA) is a useful metric because it is a cumulative measure of student performance and increasing the number of grading observations for a given student can smooth out small classroom-to-classroom variations in grading practices. Hierarchical modeling allows us to quantify the school-to-school variation in grading practices (as expressed through the GPA), accommodate missing GPA data, and effectively model the year-to-year correlation of student-level GPAs.

GPAs data from SY1718, SY1819, SY1920, and SY2021were extracted from ASPEN (the KCS student information system). The GPAs from SY1718-SY1920 were full-year GPAs reflecting grades earned during the first and second semesters of each year. The SY2021 GPAs were from the first semester only. First semester GPAs from prior academic years could not be recovered from ASPEN because of how GPA data is stored in ASPEN. GPAs generated in other districts (among transfer students) were removed from the analysis. ASPEN data was recovered using Microsoft SQL Server version 18.8.

Two hierarchical linear models (HLMs) were used in the analysis. The first model was a three-level longitudinal model used to model GPAs as a function of time (GPA_{ijk} is the end-of-the-year GPA at time i for student j at school k).

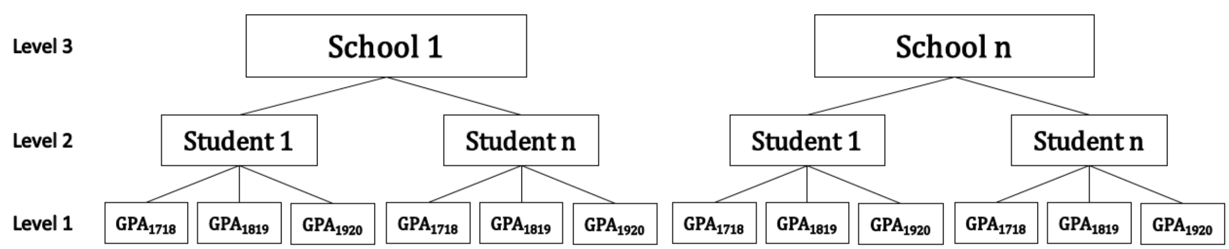

Figure 1: GPA as a Function of Time HLM Representation

Equation 1: GPA as a Function of Time HLM

$$GPA_{ijk} = \beta_{0jk} + \beta_{1jk} time_{ijk} + \sum_{demo=2}^{9} \beta_{demo} X_{ijk} + r_{ijk}$$

$$\beta_{0jk} = \gamma_{00k} + \mu_{0jk}$$

$$\beta_{1jk} = \gamma_{10k} + \mu_{1jk}$$

$$\gamma_{00k} = \delta_{000} + \upsilon_{0k}$$

$$\gamma_{10k} = \delta_{100} + \upsilon_{1k}$$

GPAs from SY1718-SY1920 were nested under students and students were nested under schools. Socio-economic (ED), special education (SpEd), ethnicity, and gender were modeled as level one fixed effects. The time-dependent slope and the intercept were allowed to vary by school and the interaction of student and school. 10,870 records among 3,890 students were included in the model.

Equation 1 was used to calculate an extrapolated SY2021 GPA for each student. The extrapolated GPA can be conceptualized as the expected GPA for a student if the student's GPA trajectory was similar in SY2021 as compared to previous years. We hypothesize that changes in the SY2021 instructional environment can be correlated with deviations in GPAs (actual semester one SY2021 GPA – extrapolated GPA). The deviation in GPA was treated as the response variable in a two-level HLM in which student-level deviations in GPA were nested under schools. Socio-economic (ED), special education (SpEd), ethnicity, and gender were modeled as level one fixed effects. A level-one fixed effect estimate was also generated for a "treatment" variable. This treatment variable indicated if a student was considered an online learner during the first semester of SY2021. Interaction effects were also estimated between the treatment variable and other level one variables.

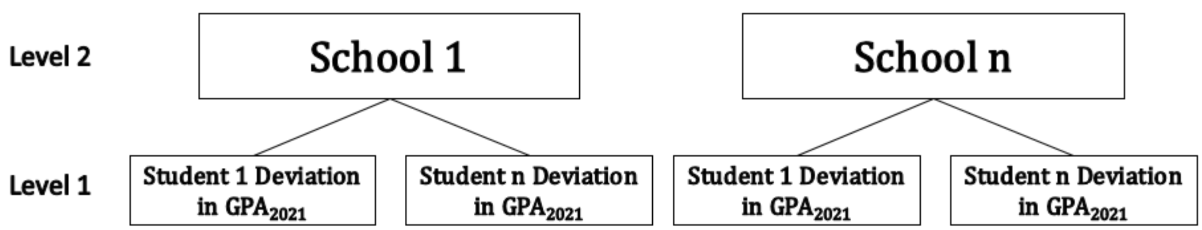

Figure 2: Deviation of SY2021 Semester 1 GPA HLM Representation

Equation 2: Deviation of SY2021 Semester 1 GPA HLM

$$GPA_{SY2021jk} - GPA_{Extrapjk} = \beta_{0k} + \beta_{1k} treatment_{jk} + \sum_{demo\,=\,2}^{9} \beta_{demo} X_{ijk} + r_{ijk}$$

$$\beta_{0k} = \gamma_{00} + \mu_{0k}$$

$$\beta_{1k} = \gamma_{10} + \mu_{1k}$$

$GPA_{Y2021jk}$ - $GPA_{Extrapjk}$ is the GPA deviation of student j in school k. 3,599 students were included in the model.

Hierarchical linear modeling was accomplished in R (version 3.6.1) running on R Studio (version 1.3.959). The lme4 package (version 1.1.21) was used to generate model parameters and extrapolated GPAs. The merTools package (version 0.5.2) was used to generate upper and lower prediction limits on the extrapolated GPAs. HLMs used the maximum likelihood procedure.

Results

The fixed effects for the extrapolated GPA model are contained in Table 1. The variances associated with Level 2 and Level 3 random effects are contained in Table 2. Level 3 (school-level) random effects are in Table 3. The baseline regression parameters apply to white, female, non-economically disadvantaged, non-special education students. These factors were chosen to define the baseline student as they were the most frequently found student characteristics in the data.

Table 1: HLM Fixed Effect Parameter Estimates, GPA vs. Time Model

Parameter	Estimate	Std. Error	t value
Intercept	3.37	0.03	111.5
Time	0.01	0.01	0.9
ED = Yes	-0.42	0.03	-14.3
SpEd = Yes	-0.37	0.03	-12.3
Ethnicity = Nat. American	-0.24	0.20	-1.2
Ethnicity = Asian	0.23	0.06	3.8
Ethnicity = Black/Afr. Amer.	-0.30	0.03	-8.5
Ethnicity = Hispanic/Latino	-0.29	0.04	-7.7
Ethnicity = Pac. Islander	0.05	0.22	0.2
Gender = Male	-0.29	0.02	-13.3

Table 2: Variance of Random Effects, GPA vs. Time Model

Level	Parameter	Variance
Student : School (Level 2)	Intercept	0.402
	Time	0.018
School (Level 3)	Intercept	0.008
	Time	0.001
Residual		0.103

Table 3: Level 3 Random Effect Estimates, GPA vs Time Model

School	Intercept	Time
Austin East High School	0.013	0.066
Bearden High School	0.052	-0.018
Career Magnet Academy	0.131	-0.049
Carter High School	0.030	-0.041
Central High School	-0.062	0.009
Farragut High School	0.172	-0.015
Fulton High School	0.005	0.043
Gibbs High School	-0.002	-0.006
Halls High School	-0.043	-0.018
Hardin Valley Academy	-0.012	-0.007
Karns High School	0.008	0.014
Knox Adaptive Education Center	-0.171	-0.003
L & N Stem Academy	0.007	0.028
Paul L. Kelley Academy	-0.061	-0.016
Powell High School	0.038	0.024
Richard Yoakley Alt	-0.044	0.005
South Doyle High School	-0.047	-0.026
West High School	-0.014	0.010

The model indicates that the mean GPA for baseline students (white female, non-ED, non-SpEd) was 3.37 among the class of SY2021. Mean GPAs associated with economically disadvantaged, special education, and male students were lower. Mean GPAs associated with Black/African American and Hispanic/Latino female students were also lower whereas mean GPAs associated with Asian female students were higher.

Q-Q plots of the model residuals suggest there may be a small amount of non-linearity in the GPA extrapolation data. Previous experience with modeling GPA suggests this is most likely attributable to the floor and ceiling effects of the GPA scale. Approximately 95% of the standardized residuals are between -2 and 2. The residual vs. predicted value plots display random patterns at both Level 1 and Level 2. These additional diagnostic procedures suggest that significant bias in the GPA extrapolation model is unlikely.

The distribution of extrapolated GPAs for the SY2021 senior cohort is contained in Figure 3. Figure 3 indicates that students who opted into virtual learning during the first semester of SY2021 were more likely to have lower extrapolated GPAs than students who opted for in-person learning. Figure 3 suggests that comparing differences in grades between online and in-person students can be misleading without controlling for previous GPAs and/or demographics.

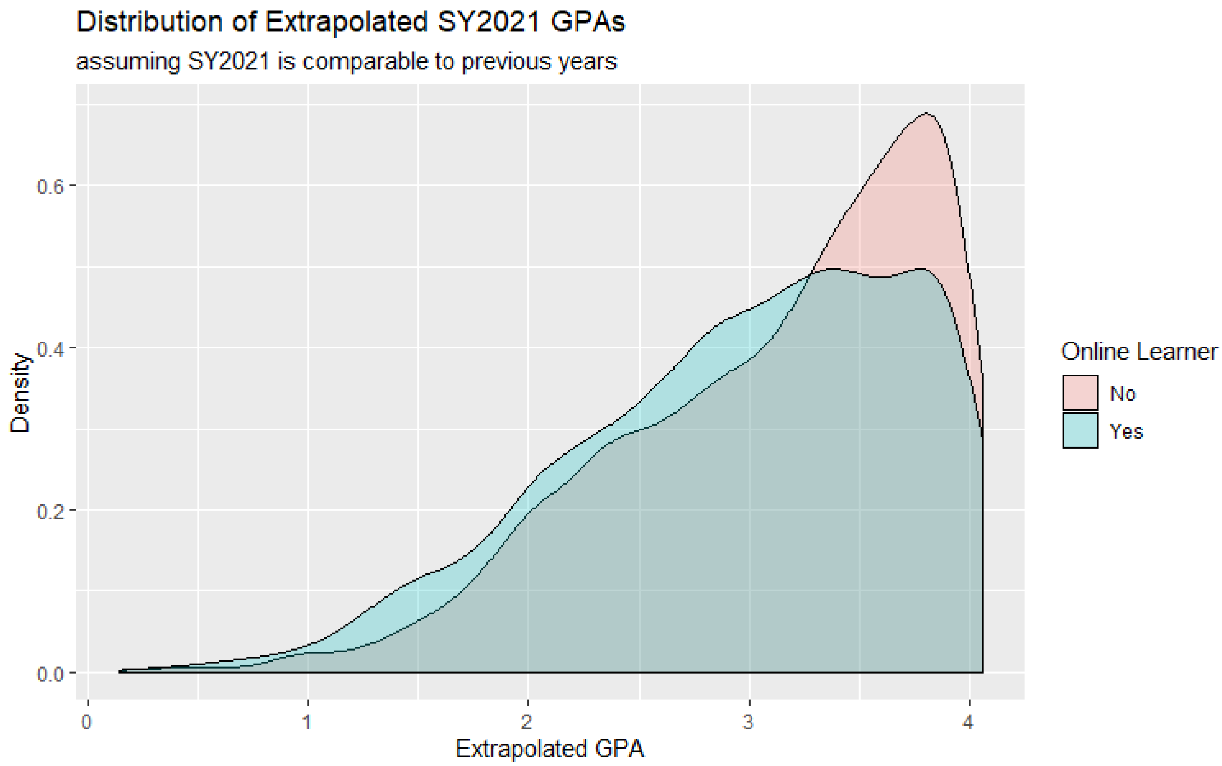

Figure 3: Distribution of Extrapolated SY2021 GPA's by Learning Modality

The fixed effects for the GPA deviation model are contained in Table 4. The variance associated with Level 2 random effects is contained in Table 5. Level 2 (school-level) random effects are in Table 6. The baseline regression parameters apply to white, female, non-economically disadvantaged, non-special education students receiving in-person instruction during the first semester of 2021.

Table 4: HLM Fixed Effect Parameter Estimates, GPA Deviation Model

Parameter	Estimate	Std. Error	t value
Intercept	-0.02	0.05	-0.4
Treatment (Online Learning = Yes)	-0.31	0.07	-4.3
ED = Yes	-0.04	0.06	-0.6
SpEd = Yes	0.01	0.04	0.3
Ethnicity = Nat. American	-0.07	0.38	-0.2
Ethnicity = Asian	0.07	0.11	0.7
Ethnicity = Black/Afr. Amer.	-0.04	0.05	-0.7
Ethnicity = Hispanic/Latino	-0.10	0.06	-1.7
Ethnicity = Pac. Islander	-0.27	0.29	-1.0
Gender = Male	0.00	0.03	0.1
Treatment * ED	-0.32	0.10	-3.4
Treatment * SpEd	-0.03	0.08	-0.4
Treatment * Ethnicity = Nat. American	0.10	0.51	0.2
Treatment * Ethnicity = Asian	0.08	0.15	0.6
Treatment * Ethnicity = Black/Afr. Amer.	-0.02	0.08	-0.2
Treatment * Ethnicity = Hispanic/Latino	0.09	0.09	1.0
Treatment * Ethnicity = Pac. Islander	1.25	0.82	1.5
Treatment * Gender = Male	-0.17	0.06	-2.7
ED = Yes * Gender = Male	-0.01	0.08	-0.1
Treatment * ED = Yes * Gender = Male	0.26	0.13	2.0

Table 5: Variance of Random Effects, GPA Deviation Model

Level	Parameter	Variance
School (Level 2)	Intercept	0.024
	Treatment	0.035
Residual		0.574

Table 6: Level 2 Random Effect Estimates, GPA Deviation Model

School	Intercept	Treatment (Online Learning)
Austin East High School	-0.293	-0.057
Bearden High School	0.086	0.090
Career Magnet Academy	0.008	-0.047
Carter High School	-0.003	-0.001
Central High School	-0.078	-0.135
Farragut High School	0.106	0.002
Fulton High School	-0.332	-0.365
Gibbs High School	0.069	-0.009
Halls High School	0.013	0.126
Hardin Valley Academy	0.098	0.098
Karns High School	0.014	-0.149
Knox Adaptive Education Center	0.104	0.108
L & N Stem Academy	-0.115	0.360
Paul L. Kelley Academy	0.117	0.093
Powell High School	-0.033	-0.164
South Doyle High School	0.081	-0.028
West High School	0.159	0.076

The model indicates that the mean deviation in GPA from the extrapolated value was -0.02 points among baseline students (white female, non-ED, non-SpEd, in-person learners). The t-value associated with the intercept suggest that this is not significantly different than zero. This finding suggests that most of the baseline students had a first semester SY2021 GPA very similar to their extrapolated estimate. The model indicates that GPAs among white, female, non-ED, non-SpEd online learners were 0.31 points lower than extrapolated.

ED status, SpEd status, gender, and ethnicities (when considered by themselves) are not correlated with significant differences in GPA deviations (when compared to the baseline group, with the possible exception of membership in the Hispanic ethnic group). However, the interaction between the learning modality and ED status and the interaction between learning modality and gender appear to be significantly correlated with larger negative deviations in GPA. The three-way interaction between learning modality, gender, and ED status seems to attenuate some of the negative two-way interaction effects (Figure 8).

Visual analysis of the school intercept and slope estimates (and standard errors) implies that there are significant school-to-school variations in how on-line instruction impacted GPAs (Figure 4 and Table 6).

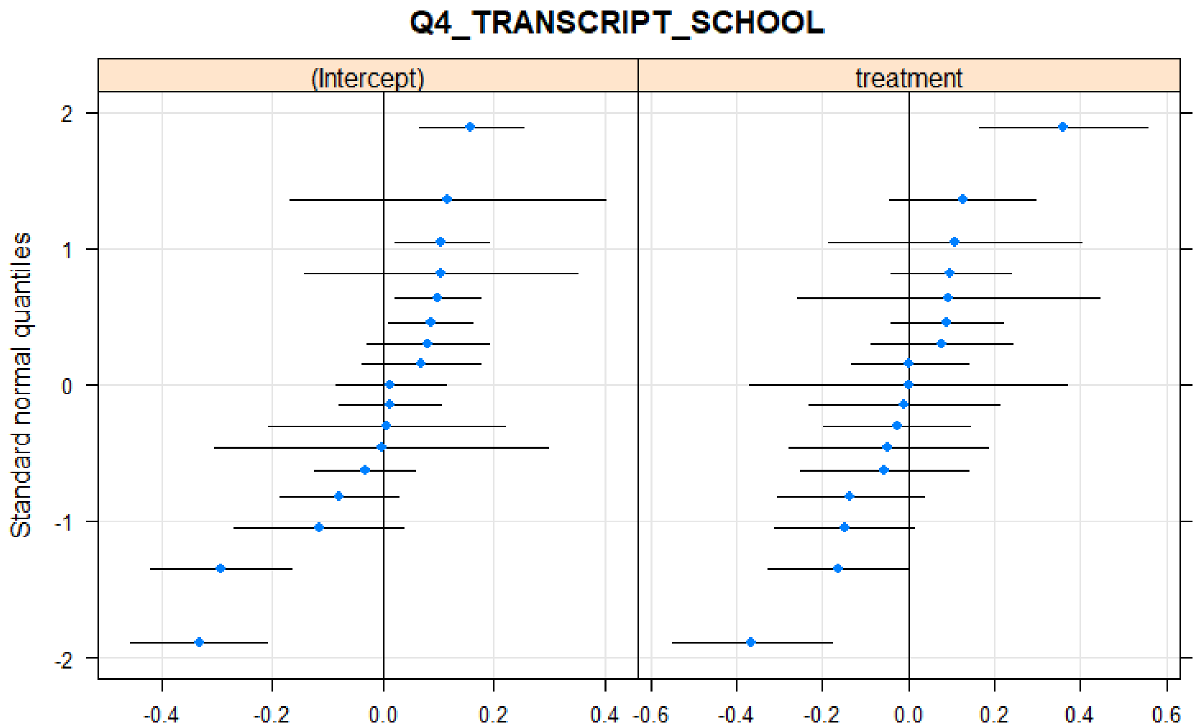

Figure 4: Random Effect Estimates with Standard Error, GPA Deviation Model

The distributions of GPA deviance (observed GPA minus extrapolated GPA) by learning modality are shown in Figure 5. The statistically significant difference in GPA deviation seems to be related to the "thickening" of the negative tail of the distribution rather than a wholesale shift in the distribution peak. This suggests that many of the students who opted for virtual learning did not experience unexpected changes in GPA as compared to their in-person peers.

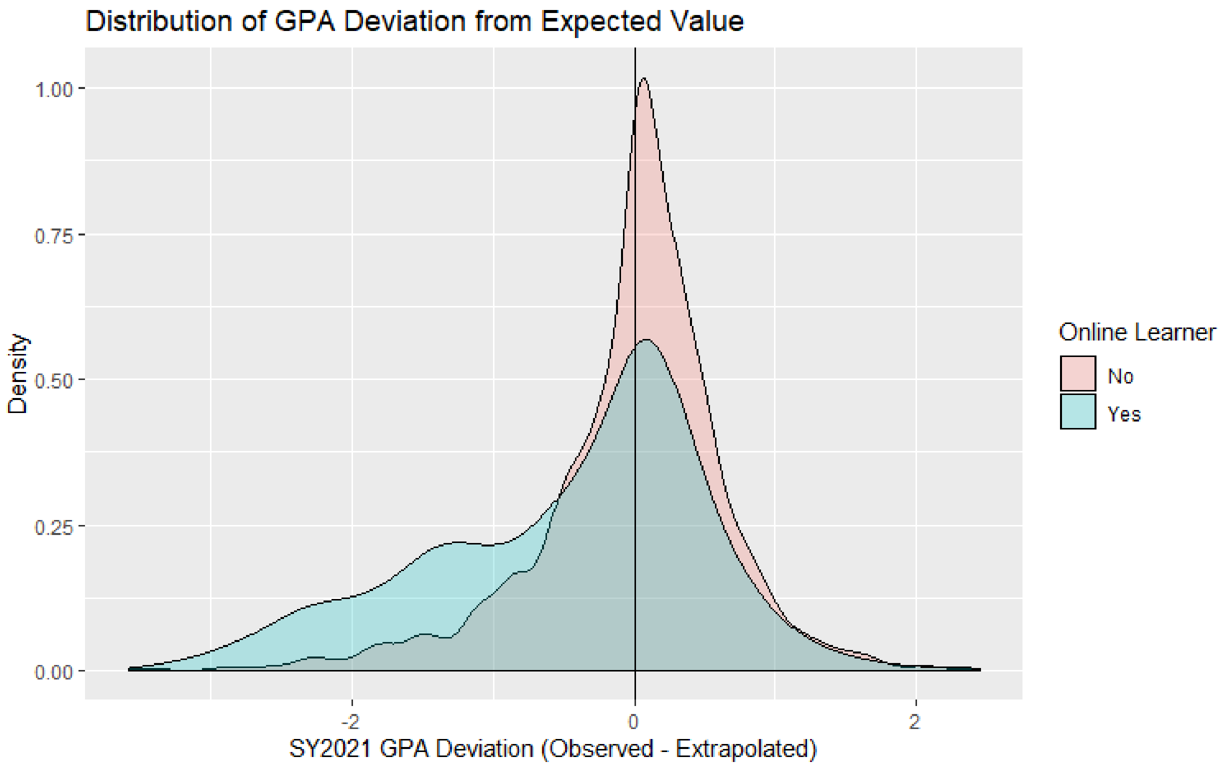

Figure 5: Distribution of GPA Deviation (Actual – Extrapolated) by Learning Modality

The results of the HLM suggest that the interaction between online learning and economically disadvantaged status is significantly correlated with negative deviance in GPA. Figure 6 shows the distributions of deviation in GPA by ED status among online learners provides some empirical confirmation that most of the negative impact on GPA among online learners concentrates among students who are classified as economically disadvantaged.

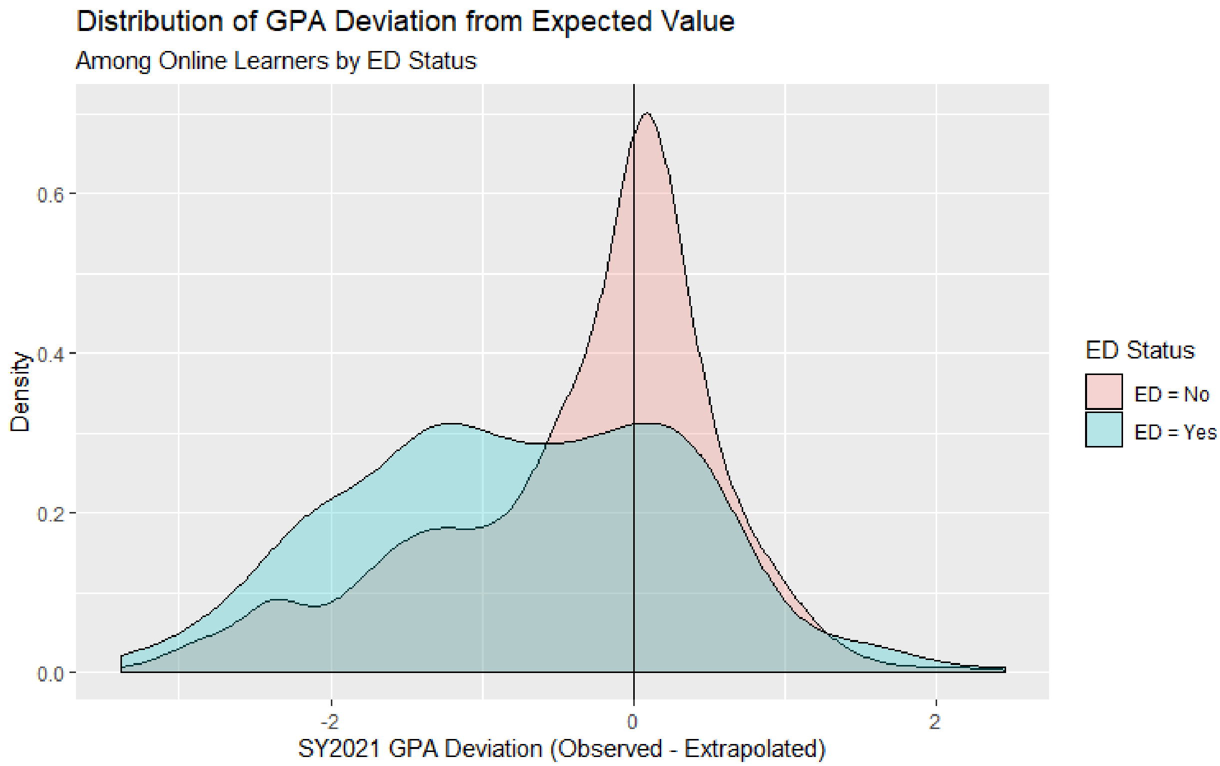

Figure 6: Distribution of GPA Deviation (Actual – Extrapolated) Among Online Learners by ED Status

Figure 6 also indicates that the "ED = Yes" deviance distribution exhibits two peaks. This suggests that participating in virtual learning may impact groups of ED students differently. The peak to the right implies that some online ED students have not experienced negative GPA deviance. The peak to the left implies there may be an equally large population of online ED students who have experienced significant negative deviation in GPA. Identifying fundamental differences among these groups may help KCS adjust online programming to zero out the negative effects on GPA associated with virtual learning.

Plots related to other significant interactions are available in Figures 7 and 8. Figure 7 is related to the online instruction and gender interaction. Figure 8 is related to the three-way interaction between online instruction, ED status, and gender. Figures 7 and 8 also imply that a relatively large group of online students have not experienced changes in GPA after opting for virtual learning. Figures 7 and 8 also exhibit bi-modal peaks similar to Figure 6.

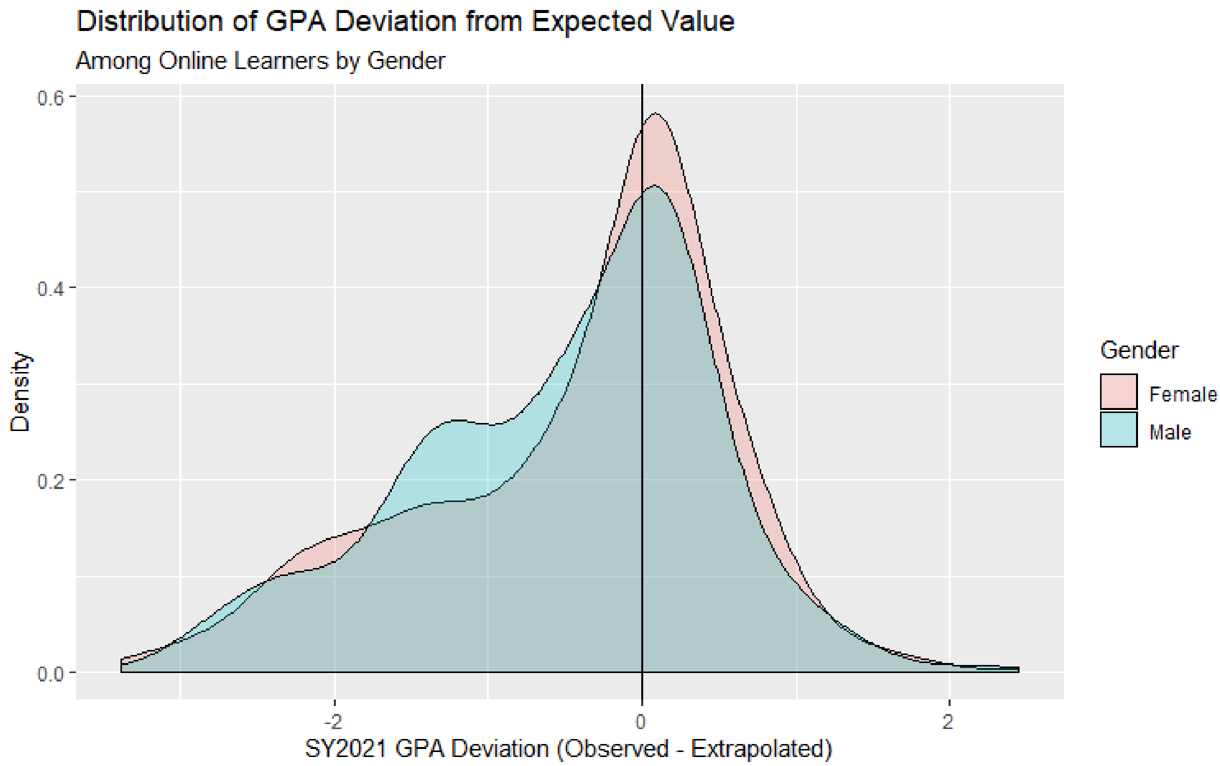

Figure 7: Distribution of GPA Deviation (Actual – Extrapolated) Among Online Learners by Gender

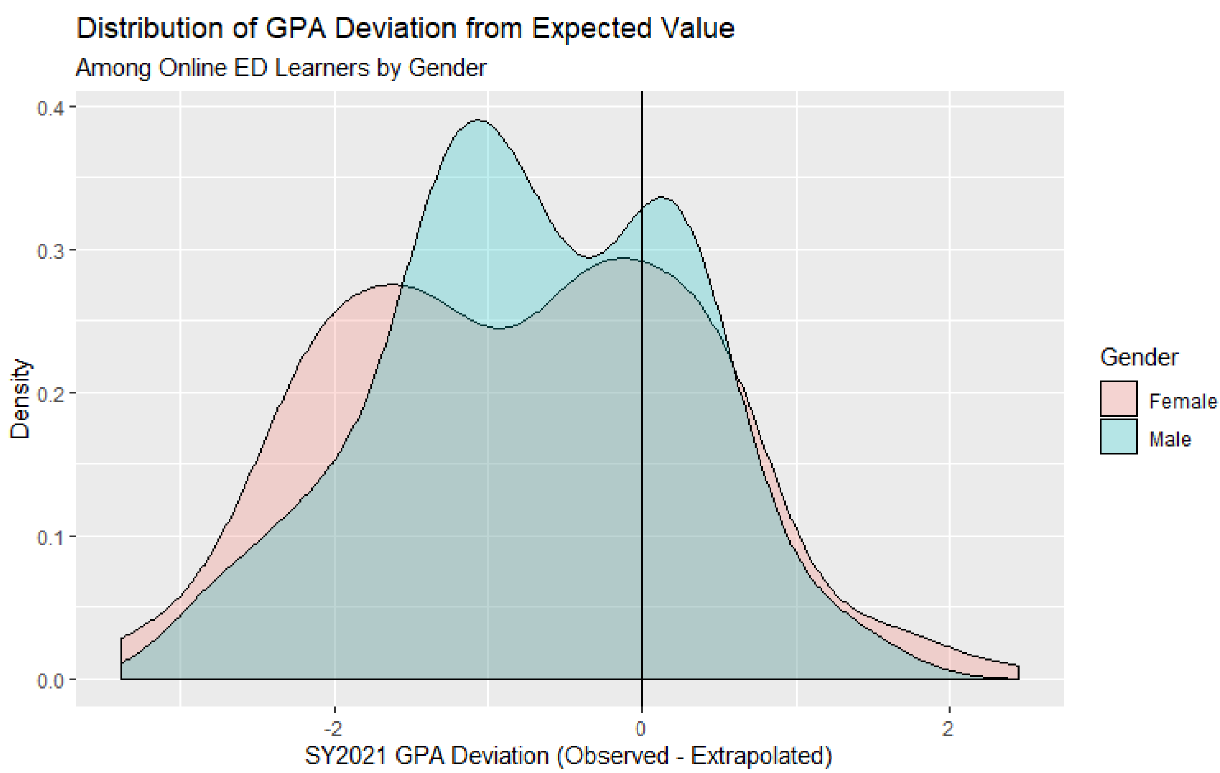

Figure 8: Distribution of GPA Deviation (Actual – Extrapolated) Among ED Online Learners by Gender

Conclusions & Considerations

The results of this regression analysis suggest that students who opted for online learning during the first semester of SY2021 were more likely to experience negative changes to their GPA than students who opted for in-person instruction. Conceptually, the magnitude of the mean decrease in GPA for online learners was the equivalent to losing 1.5 letter grades in any one course of a student's four-course block schedule (i.e., moving from a B average to a C- average in one of four scheduled courses). However, visual inspection of the data suggests that negative impacts on GPA could be related to undocumented student characteristics.

The output from the regression models can be used to prioritize follow-up research efforts. The random effect parameter estimates can indicate where school-level impacts of online learning (on student GPAs) are significantly different. Instructional leaders can prioritize studying practices at schools with larger positive effects on GPA and providing support at schools with larger negative effects. Analysis of the student-level residuals (from the HLM models) may provide starting points for future qualitative data collection. Interviews with students from different parts of the GPA deviance distribution may shed light on factors that impact student success in the online environment. Case or ethnographic studies among student outliers (in either tail of the distribution) may provide a more nuanced and contextual understanding of online and in-person student experience.