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Essays on the Economics of Education

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ABSTRACT

ESSAYS ON THE ECONOMICS OF EDUCATION

By

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Major Department: Economics

This dissertation includes three chapters relating to the economics of education. The first two chapters analyze education during the COVID-19 pandemic, with one investigating the impacts of a summer school program and the other looking at teacher labor markets before and after the pandemic. The third chapter, co-authored with Caroline Lamprecht, evaluates the effectiveness of a classroom game for teaching students about environmental policy.

The first chapter of this dissertation analyses the impacts of a summer school program using a regression discontinuity design. After the COVID-19 pandemic forced schools to close and students began remote learning, many researchers have observed a corresponding decline in student achievement or "learning loss." In this chapter I study a school district that implemented a summer school program in the summer of 2021 with the intent of helping students to catch up to pre-pandemic relative achievement levels. As the district used specific invitation criteria, I am able to employ a regression discontinuity approach and find that the program had minimal impacts for students near the invitation threshold. Further, I find that the program had low participation rates in general, though participation rates were higher among invitees from disadvantaged backgrounds.

The second chapter is a descriptive analysis of teacher labor markets during the COVID-19 pandemic. During the pandemic, teachers reported higher levels of burnout and districts reported difficulties with hiring and retaining teachers. I compare hiring and retention patterns from before the start of the pandemic to those and after the pandemic and find that that pandemic-era challenges only led to temporary changes in hiring and retention patterns. I also employ a series of logistic regressions to understand which teacher characteristics are most closely related to teacher attrition and mobility decisions before and during the pandemic. These analyses reinforce the findings of the descriptive analysis; attrition trends returned to pre-pandemic levels in the second pandemic year.

The third chapter in this dissertation employs an experimental approach to evaluate the effectiveness of a classroom game for teaching students about environmental policy. Students in Principles of Economics courses were assigned to either a treatment group that played the game during class or to a control group which did not play the game. Students were asked to complete two questionnaires which included survey questions and a quiz on cap-and-trade policies. We find that playing the game had modest impacts on student knowledge of cap-and-trade policy. However, we do find evidence that the game may have boosted student engagement in learning economics. Our study suggests that classroom games should be used along with traditional lectures to boost student engagement and interest in learning economics, though games alone may not be the most effective method for teaching economic concepts.

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SARAH STERLING KING

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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1.1 Introduction

During the spring semester of the 2019-20 school year, the COVID-19 pandemic forced schools across the country to switch to remote learning. For many schools, remote learning in some fashion continued into the fall 2021 semester and beyond. For many students, remote instruction is not as effective as traditional face-to-face instruction; combined with the impacts of crisis learning, we know that crisis remote learning led to lower student achievement growth which necessitated acceleration programs to help get students back on track (CREDO 2015; Ahn and McEachin 2017; Dorn et. al. 2020; Kuhfeld et. al. 2022). In this chapter, I analyze the efficacy of one such recovery effort: a 2021 summer school program implemented in a large urban school district in Georgia. The summer school program targeted students who had failed courses or were performing below grade level on exams with the hope that additional instruction would help students to get caught up. This chapter examines the effectiveness of this 2021 summer school program on student performance using a regression discontinuity design, and specifically considers students in elementary and middle grades as these are the grades levels where students were invited to summer school based on measurable criteria and make up the majority of attendees. I find that invitation to the program had minimal impacts for students in the middle of the test score distribution. Further, I find that attendance is significantly related to student characteristics such as family income.

1.1.1 Learning Loss

The COVID-19 pandemic presented a significant shock to learning for students around the world. Most studies of student achievement growth since the start of the pandemic have found lower achievement growth compared to the pre-pandemic period and compared to other schooling disruptions in the past (Pier et. al., 2021; Kuhfeld et. al., 2022). Specifically, studies have reported reductions in student achievement growth in the spring of 2020 that are comparable to the amount of time that students lost in face-to-face instruction (Dorn et. al., 2020; Engzell et. al., 2021). The reduction in achievement growth may also have important equity implications as the pandemic has continued. For instance, authors have noted that non-white students may have been more likely to receive remote education for longer which may have exacerbated pre-pandemic achievement gaps (Darling-Aduana, 2022). Other studies have noted widening achievement gaps, especially among high- and low-income students (Dorn et. al., 2020; Lewis et. al., 2021; Bailey et. al., 2021; Pier et. al., 2021; West & Lake, 2021; EmpowerK12, 2021; Kuhfeld et. al., 2022).

Learning loss is a concern to educators even outside of the pandemic context; further, understanding learning loss in other contexts provides some insight as to why the pandemic was so impactful for students. In general, researchers have found lower achievement by students following summer break, with the decline of test scores being close to the equivalent of one month of learning (Cooper et. al., 1996; Quinn & Polikoff, 2017). Summer learning loss appears to be greater in math than in reading, though there are mixed results regarding learning loss for different grade levels (Hanover Research, 2020). In addition, researchers have noted that learning loss may be an issue of equity and that it may differ by subgroups, though the evidence is inconclusive. While it is known that achievement gaps grow during the school year, there is mixed evidence regarding whether or not they also grow during the summer. Some studies find that income-based achievement gaps grow for reading, while others find race-based achievement gaps shrink during the summer or there is no significant change in achievement gaps by subgroup (Atteberry & McEachin, 2021; Kuhfeld et. al., 2021). There is also a significant strand of literature on the origin of achievement gaps; most research suggests that gaps are present before children even begin school. Research on whether these gaps grow during schooling is inconclusive (von Hippel et. al., 2018; von Hippel & Hamrock, 2019). While this chapter considers a program during the COVID-19 pandemic, it also has implications for summer programs in general and thus gives rise to the importance of understanding summer learning loss. In particular, this study is focused on a diverse district which suggests the findings are applicable to many other districts. Further, while pre-pandemic summer programs focused on students at risk of being retained, this program targeted students in the bottom half of the achievement distribution. This study compares students just below and those just above the invitation cutoff, which means one can draw conclusions regarding the efficacy of summer programs for students in the middle of the achievement distribution. Finally, while this study is considering a summer program during the pandemic, the results from this district are likely more generalizable than results from other districts given that the district had previously returned to face-to-face instruction early in the 2020-21 school year.

While learning loss has mostly been studied within the context of summer breaks, there has also been some research on learning loss associated with reductions in instruction due to absenteeism or weather-related school closures. Prior research finds that reducing student absences, particularly unexcused absences, has a significant impact on student achievement, especially in math (Gottfried, 2009; Gottfried, 2010; Gottfried, 2011; Aucejo & Romano, 2016; Santibanez & Guarino, 2020). Chronic absenteeism has been linked to greater student disruptions and therefore negative spillover effects for other students in the class (Lazear, 2001; Gottfried, 2019). While inclement weather has been shown to reduce student achievement, there is mixed evidence whether this effect is due to school closures or to weather-related absences and disruptions in students' personal lives (Holmes, 2002; Marcotte, 2006; Goodman, 2015).

Additionally, researchers have explored the impacts of other crisis scenarios. Jaume and Willen (2019) examined the impact of teacher strikes in Argentina which led to the closing of schools on later labor market outcomes and found worse outcomes for students who were impacted by school closures, especially in earlier grades. Another external shock to education was Hurricanes Katrina and Rita, which impacted the gulf coast of the United States. The hurricanes forced many families to evacuate which meant that many students had to change schools or go without schooling. The literature on student achievement impacts of this shock suggests that students obtained lower test scores after the storms and that there was a gap between students who were and were not displaced as a result of the storms, with mixed results on persistence of these effects (Ward et. al., 2008; Sacerdote, 2012). Thus, the literature on summer learning loss and learning loss in other contexts suggests that time in school is important for student achievement. While the pandemic presented a major disruption to student learning, disruptions may happen at other times so understanding their impacts and the impacts of potential remediation programs may have implications beyond the pandemic.

1.1.2 Summer Programs

Most of the literature on summer programs suggests that effects on student learning are modest at best, with greater impacts in math than in reading (Augustine et al., 2016; Lynch & Kim, 2017; Sharp, 2018; Hanover Research, 2020; Prettyman & Sass, 2021; Pyne et. al., 2021). Further, targeted programs, programs that are at least five weeks in duration, and programs with smaller class sizes, have been found to yield the greatest positive impacts (Sharp, 2018; McCombs & Augustine, 2021; Pyne et. al., 2021). However, Katzir et. al. (2013) found that, while effective, summer school programs were not as effective in boosting student achievement as after-school programs or a combination of the two.

Studies analyzing impacts for subgroups have found inconclusive results, with mixed evidence regarding students from households in different income categories, but greater impacts for males than for females and larger effects for Latino students (Quinn & Polikoff, 2017; Pyne et. al., 2021). Finally, while many studies have reported low attendance for summer programs, attendance is greater for programs that offer enrichment activities and other camp-like activities (Augustine et al., 2016; McCombs & Augustine, 2021). This study intends to contribute to the limited extant literature on heterogenous effects of summer programming by exploring the impacts of a pandemic-era summer program on various student subgroups, with the goal of understanding whether the program was successful at closing achievement gaps.

1.1.3 The Current Study

The current study examines a summer school program administered by a large urban school district in Georgia. Students were initially invited to the program if they met certain eligibility requirements such as a failing course grade or a below grade level score on a formative assessment. However, attendance was not required of invited students and students who were not initially invited were still able to opt into the program after the initial eligibility designations were made, but before the program began. The eligibility criteria give rise to a fuzzy regression discontinuity analysis where students who were barely eligible can be compared to students who were barely ineligible. This study expands on the current literature by exploring the effectiveness of summer school on student achievement for students in the middle of the test score distribution (rather than for the lowest achieving students) and by exploring the potential differential impact of summer programing across subgroups of students. Given that summer school programs before the pandemic traditionally targeted students at the bottom of the test score distribution, the RD approach in this context allows us to understand whether summer school has different impacts for average students rather than low-performing students. Further, this study uses detailed administrative data which allows for a causal estimate of the efficacy of the program. Thus, the goal of this study is not only to provide guidance to the school district and to other school districts seeking to accelerate student learning but also to contribute to the larger literature on summer programs. While the program of interest was implemented during the COVID-19 pandemic as a response to lowered achievement growth, the implications of this study can generalize to other contexts to provide researchers and policymakers a better understanding of summer programs.

1.2 Institutional Context

1.2.1 The Summer Program

Following a year of virtual and hybrid learning, many school districts including the one of interest offered summer school programs to help students to catch up. The summer program of interest, implemented in the summer of 2021, was open to students in all grade levels and used certain criteria to invite students to participate in the program. The program was intended to provide additional instruction in certain subject areas based on student needs for students in elementary and middle grades.[1] Most elementary and middle school sessions, except for middle school world language instruction, were offered in a face-to-face format.[2] This chapter focuses

[1] For high school students, the program was intended for students to make up failed or incomplete courses, or for students to take additional courses for the purpose of acceleration. Most of the high school offerings were virtual.
[2] While middle school world language instruction was delivered virtually, middle school world language eligibility does not provide a measurable criterion by which an analysis can be conducted. Further, the majority of middle school attendees were invited due to test scores and thus attended the program in-person.

on the elementary and middle school face-to-face programs as these were based on measurable invitation criteria and constitute the majority of attendees.

The district offered sessions in both June and July with all grades having the option to participate in June sessions and all grades except for middle grades having the option of participating in a July session. Further, elementary had the option of registering for just one or both sessions. While high school students received instruction in the specific course needed, elementary and middle school students received more generalized instruction. Elementary students received instruction in both math and reading at all sessions; middle school students registered for instruction in a specific subject area, though reading, English-Language Arts, science, and social studies were delivered together, and some students received instruction in math along with another subject area.

While receiving academic instruction, the summer school program also provided students with additional holistic benefits. Specifically, students who attended summer school received two free meals, including breakfast and lunch, and most received free transportation to face-to-face sessions. During the pandemic, all students had been eligible for free meals, though free or reduced-price meal benefits, whether for specific students or all students, typically stop during the summer months, thus this may have been an important benefit of participation. In addition, the district provided families with the option to pick up meals during the summer, though this option was only available at a limited number of locations, and families had to pick up and subsequently store and make food for a full week. The program had no tuition except for high school students who wanted to do acceleration coursework.

1.2.2 Summer School Invitation Criteria

The school district used 12 different eligibility criteria to determine initial eligibility for summer school; these criteria varied by grade level (see table A1). The two most frequently used criteria were scores on formative assessments and course grades. To be eligible based on test scores, a student in elementary or middle school must have scored at a level deemed "below grade level" on the middle-of-year iReady formative assessment[3] (formative assessment scores were not used to determine eligibility for high school students as students did not take the iReady test). For an elementary student to be eligible based on course grades, the student must either have an "incomplete" grade on their transcript in reading or math, therefore having the opportunity to make up this course in summer school, or they must have a current grade below a 70 percent (i.e., failing) at the time of invitation. For a middle or high school student to be eligible based on course grades, the student must have a failing (lower than a 70 percent) or "incomplete" course grade on their transcript from spring 2020, fall 2020, or spring 2021, with middle school students needing two semesters of a failing grade in the course or a single semester of a failing grade in a foreign language course, therefore giving students the opportunity to make up these credits in summer school.

There were a few other criteria for which I do not have the necessary data, including some criteria that are more subjective and therefore do not have a clean cutoff to examine. One criterion was only for students in kindergarten or first grade and was for students who opted for remote instruction during the 2020-21 school year and either had an attendance rate below 51 percent of classes or an assignment completion rate below 80 percent. While this criterion does provide clean cutoffs and I do know which students were eligible for this reason, the school

[3] This test was administered at the start of the spring semester of the 2020-21 school year.

district was unable to provide data as this was based on teacher reporting and actual student attendance or assignment completion were not tracked in a way that the district would have the information. Additional reasons that a student could attend summer school were by teacher recommendation, retention consideration for elementary and middle school students, or for high school students, or course acceleration. Not only was the data for these criteria not tracked, but they are measures for which there is no consistently used underlying scale and therefore cannot be included in a regression discontinuity analysis. The final criterion for summer school eligibility related to students on an adapted curriculum such as a special education program. These students could be eligible based on not meeting certain objectives, incomplete courses, and low engagement like other students, but data for these elements is not available and therefore cannot be used in this analysis. In addition to the criteria for initial invitation to the summer school program, the district opened up registration to all students after realizing that there would be a low rate of registration among those who were invited. The main analysis focuses on students who were initially invited to participate in the program.

1.3 Methodology

This study employs a regression discontinuity design that exploits eligibility criteria used for a 2021 summer school program in a large urban school district. Specifically, the study exploits criteria relating to student grades and student scores on a formative assessment. This analysis also explores the impact of the program on various student subgroups.

1.3.1 Data and Sample

This study uses proprietary, high-quality administrative data which was provided by the school district of interest. The data includes information on student characteristics, achievement including student scores on the iReady formative assessment and course grades, and summer school performance and attendance (if applicable). A total of 38,175 students were deemed eligible by the initial eligibility criteria, including test scores, remote attendance (for kindergarten and first grade), and course grades, with additional students having the option to opt into the summer program by request or teacher recommendation. Of those, 30,603 were in elementary or middle school which accounts for 53% of all elementary and middle school students in the district. A total of 8,874 students actually attended the summer school program with 6,967 (78.5%) being students who were initially deemed eligible and 1,907 (21.5%) being students who opted into the program. Of the attendees, 5,731 were in grades 1-8, accounting for 10.9% of all students in those grade levels, with 87.9% of those students being initially invited to participate. Therefore, a total of 30,909 students were deemed eligible and initially invited to the program but did not attend summer school, with 79% of those students being in grades 1-8.

The primary way that students in grades 1 through 8 were deemed as eligible for summer school was by scoring below grade level on an iReady assessment. A total of 29,469 (77.2% of those deemed eligible for any reason, and 96.8% of all in grades 1 through 8) students were deemed eligible based on iReady scores, with 5,038 (17.2%) of those students actually attending summer school. Among elementary and middle school students, the majority of attendees came from elementary grades with grades 2-5 having an average of 826 attendees each versus grades 6-8 which have an average of 537 attendees each. Each grade level had a similar number of students who were initially invited to attend.

Eligibility by course grades was the only way that high school students could be initially deemed as eligible and was a significant way by which middle school students were deemed as eligible. However, the number of high school students for whom complete data is available is very low so they are omitted from the analysis. In addition, many high school students who attended summer school did so simply to make up credits that may not be relevant for future courses or to accelerate. As for middle school students, approximately 26% of those who were initially invited were invited due to course grades, though only 3% were invited only due to course grades. I focus the analysis on eligibility by test scores though I do perform a secondary analysis which considers eligibility due to failing course grades for middle school students.

1.3.2 Empirical Method

This study employs a "fuzzy" regression discontinuity design (RDD) and considers student formative test scores as the underlying continuous variable. A regression discontinuity design considers observations that are near some cutoff and compares those just below and just above with the assumption that these observations should be fairly similar other than their assignment to treatment (Hahn et. al., 2001; Imbens & Lemieux, 2008; Lee & Lemieux, 2010). In this case, the cutoff is a below-grade-level score on a student's iReady assessment, determined by a student's grade level and subject area. A "fuzzy" RDD is used when assignment to the treatment is not perfectly determined by the observable threshold. In this study, the "fuzzy" design is used given that the threshold of a below-grade-level score was not a perfect indicator of a student being deemed eligible due to some unreported exceptions and additional criteria. Therefore, the FRD measures the difference in test scores where there is a discontinuity, or a non-trivial jump, in the probability of assignment, which in this case is eligibility for summer school based on iReady scores. Further, I employ an intent-to-treat (ITT) approach. The ITT approach is important as there may be selection bias in an eligible student opting to attend summer school. However, a limitation of this approach is that the effect of the treatment itself is not estimated.

As students in grades 1 through 8 could be deemed eligible for summer school based on iReady test scores, the outcomes of interest are iReady scores for the beginning of year test of the 2021-22 school year in math and reading. Therefore, the model used for both the math and reading test score analyses is as follows:

$$iReadyF22_i = \alpha + \beta iReadyW21_i + \tau SS_i + \gamma iReadyW21_i SS_i + \delta X_i + \epsilon_i,$$

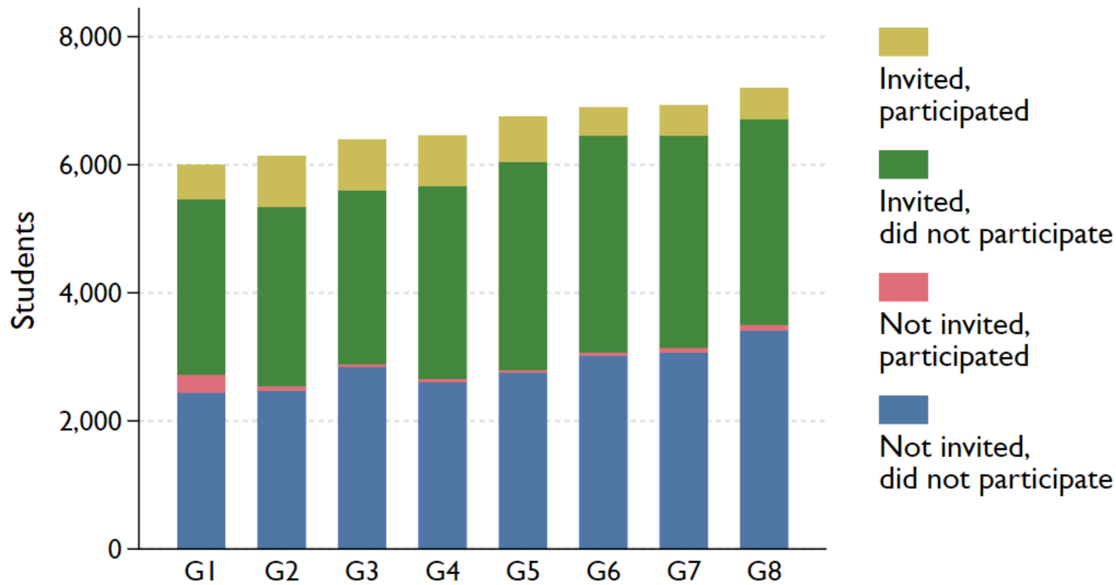
where *iReadyF22* is a student i's iReady test score at the beginning of the fall semester of the 2021-22 school year, *iReadyW21* is a student i's iReady test score in the middle of the 2020-21 school year, *SS* denotes whether a student *i* was invited to summer school based on iReady scores, *X* is a vector of controls, and ϵ_i is an error term. The coefficient of interest is τ which represents the average treatment effect of receiving an invitation to the program.

1.4 Results

1.4.1 Descriptive Analyses

Overall, participation was low for the summer school program with only 17% of invited students actually participating in the program and only 11% of all elementary and middle school students participating (compared to 56% of 1-8 students receiving invitations to participate). Figure 1.1 shows participation and invitation by grade level with the corresponding table (Table A2) available in the appendix.

Figure 1.1. Summer School Invitation and Participation by Grade Level



Notes. Figure shows the number of students who received an invitation due to having a below grade level score on the middle of year iReady assessment in the 2020-21 school year and their subsequent participation in summer school.

I first observe that there are a similar number of students who were invited to participate in each grade level, though students in elementary grades were about twice as likely to attend than students in middle grades. I then observe differences in eligibility and participation due to below grade level iReady scores by gender, free or reduced-price lunch (FRPL) status, and English-language learner (ELL) status for students in grades 1 through 8, shown in table 1.1. I choose the FRPL and ELL covariates as they represent specific barriers that students may face. In particular, FRPL status is a commonly used proxy for the family income of a student which may be related to additional supports that a student may need during the summer.

Table 1.1. Summer School Invitation and Participation by Subgroup

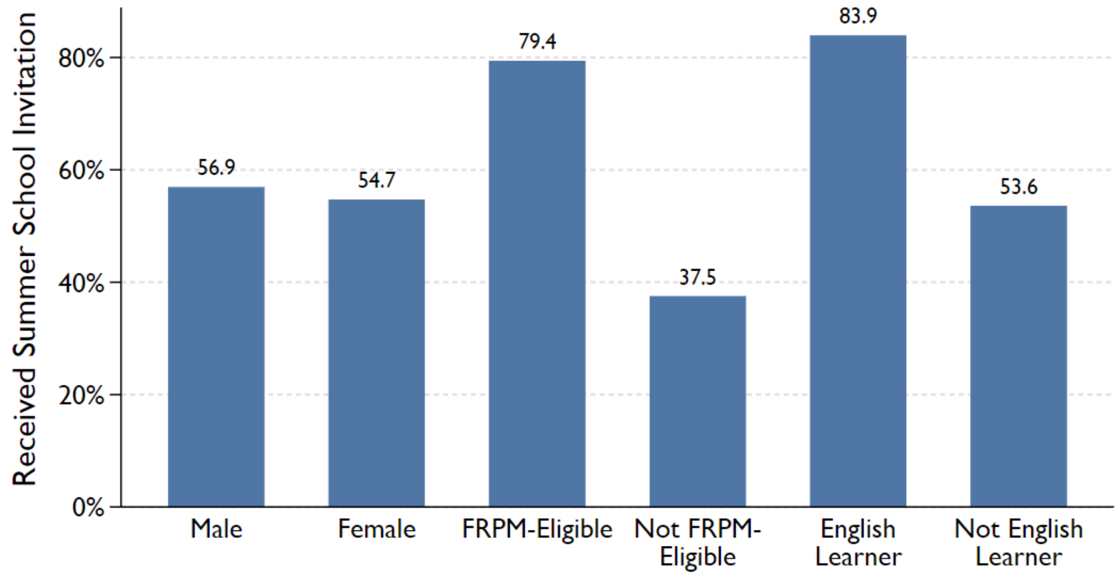
	Gender		FRPM Eligibility Status		English Learner Status		
	Female	Male	Not Eligible	Eligible	Not ELL	ELL	Total
Eligible and Attended	47.1%	52.9%	19.9%	80.1%	82.1%	17.9%	5,038
Eligible and Not Attended	48.5%	51.5%	41.3%	58.7%	90.4%	9.6%	24,431
Not Eligible and Attended	48.8%	51.2%	36.5%	63.5%	89.0%	11.0%	693
Not Eligible and Not Attended	50.5%	49.6%	80.8%	19.2%	97.6%	2.4%	22,623
Total	25,993	26,792	29,641	23,144	48,926	3,859	52,785

Notes. Percentages denote the percentage of students in each subgroup who received an invitation due to below grade level score on the middle of year iReady assessment in the 2020-21 school year.

Male and female students each made up about half of all participants in the summer school program (47% female, 53% male). The majority of participants were eligible for free or reduced-price meals (78%), compared to just 44% of elementary and middle school students in the district who were FRPM eligible. English learners also made up a disproportionate amount of participants with 17% of participants being English learners compared to only 7% of 1st through 8th graders in the district being English learners.

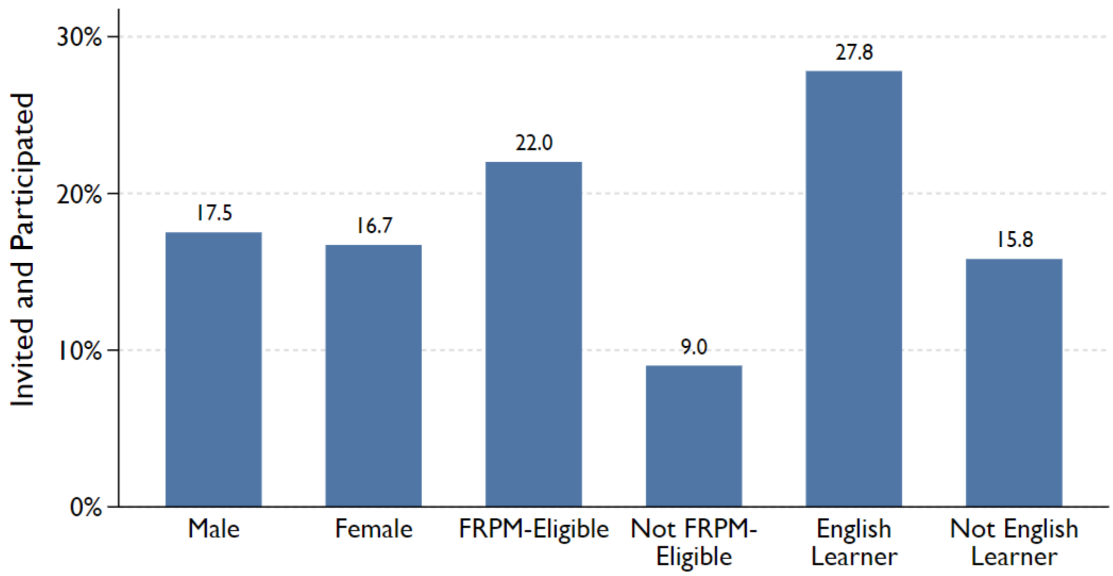
I break these statistics down further to understand if these participation rates were due to differences in invitation (i.e., existing achievement differences which led to invitation to the program) in figure 1.2.

Figure 1.2. Summer School Invitation by Subgroup



While similar proportions of male (57%) and female (55%) were initially invited to the program, I saw much different proportions for other subgroups. For FRPM-eligible students, 79% were invited to participate, compared to 38% of all students who were not FRPM-eligible. Further, 88% of all English learners were invited to participate, compared to just 54% of native English speakers. I then can consider participation conditional on invitation, shown in figure 1.3.

Figure 1.3. Summer School Participation among Invitees



Notes. Percentages denote the percentage of students in each subgroup who were invited due to having a below grade level iReady score who opted to attend the summer program.

Again, comparable proportions of male (18%) and female (17%) invitees opted to participate. As for FRPM-eligible students, 22% of invitees opted to participate, compared to only 9% of non-FRPM eligible invitees. Finally, 28% of English learners who were invited opted to participate, compared to 16% of English speakers.

I also consider whether test scores are related to the likelihood of receiving an invitation to summer school, shown in figure 1.4, and whether test scores are related to the likelihood that a student participated in the program, shown in figure 1.5.

Figure 1.4. Relationship between Student Middle of Year Test Scores and the Probability of Receiving an Invitation to Summer School

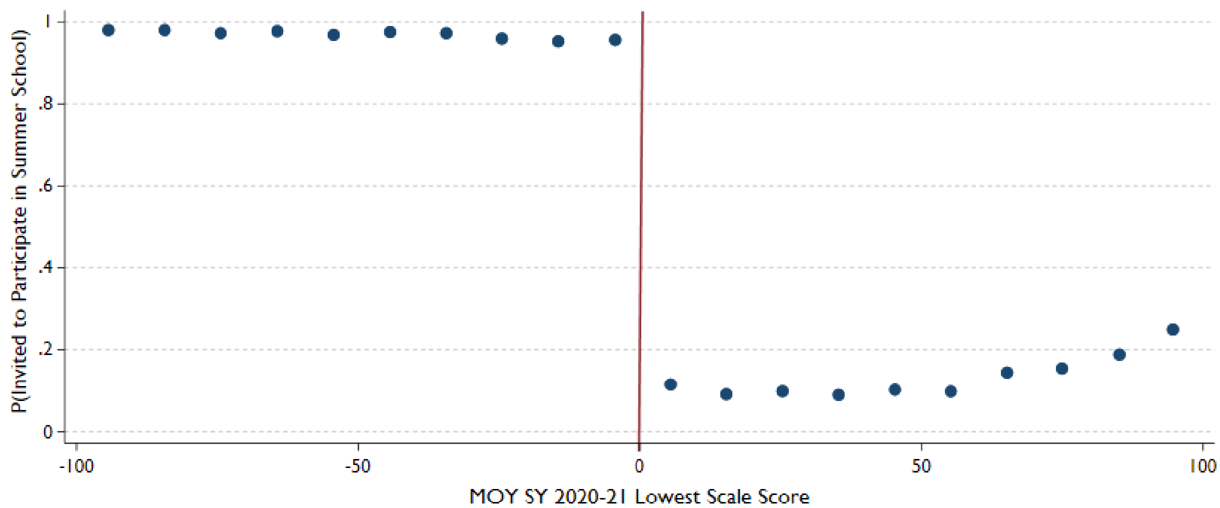
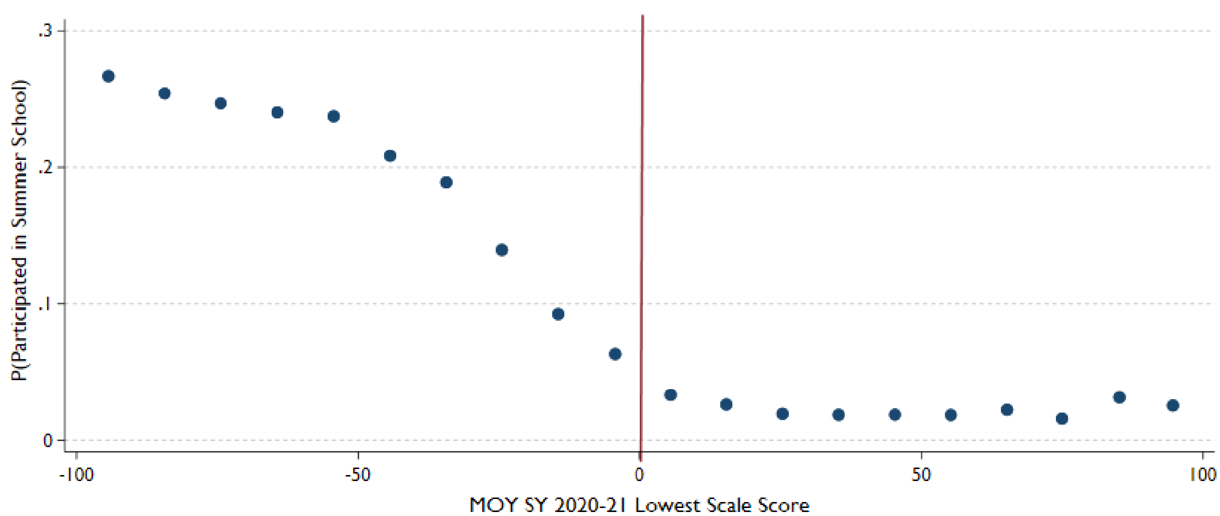


Figure 1.5. Relationship between Student Middle-of-Year Test Scores and the Probability of Attending Summer School



I observe a large discontinuity in the likelihood that a student receives an invitation to participate in summer school at the below grade level threshold where students below the threshold have a probability near 1 of receiving an invitation. Further, while there is less of a discontinuity regarding participation in summer school, I do observe that the likelihood of attending decreases as student test scores increase.

Further, given the observed participation rates for various groups of students, I conduct first stage descriptive analyses using OLS models to better understand which students opted to participate in the summer program and to check for a relationship between invitation and participation, shown in table 1.2.

Table 1.2. Descriptive Statistics of Summer School Participants

			Bandwidth	
			Full Sample	(-20, 20)
FRPM	0.1431***	0.0958***	0.0869***	0.0639***
	(0.003)	(0.003)	(0.003)	(0.004)
Female	-0.0064	-0.0006	-0.001	-0.0024
	(0.003)	(0.003)	(0.003)	(0.003)
ELL	0.1211***	0.0949***	0.0938***	0.0931***
	(0.005)	(0.006)	(0.005)	(0.010)
MOY Lowest		-0.0009***	-0.0007***	-0.0009***
		(0.000)	(.000)	(0.005)
Invitation			0.0522***	0.0281***
			(0.004)	(0.005)
N	52,785	46,404	46,404	16,876

Notes. Standard deviations in parentheses. Asterisks denote statistical significance, *** p<0.001, ** p<0.005, * p<0.01.

As expected from the summary statistics, being eligible for free or reduced-price meals increased the likelihood that a student would attend the program by approximately 14% and being an English learner increased the likelihood that a student would attend by approximately 12%. These figures remain significant even when controlling for a student's middle-of-year iReady score and invitation. However, gender is not a significant predictor of whether a student would attend the program. In addition, I consider the impact of winter test scores on the likelihood of participation and find that lower test scores significantly increased the likelihood of participating with 10 scale points lower leading to a 1% increase in the likelihood of participating, conditional on invitation and other observed characteristics. Finally, I consider the first stage of whether invitation is related to the likelihood that a student participated in summer school. I find that receiving an invitation to the summer program increases the likelihood that a student participated in the program by 5%. Further, given that the regression discontinuity design considers a subset of students near the threshold of invitation, I run the first stage with a bandwidth of 20 and find similar levels of significance. These results reinforce what is shown in figures 1.4 and 1.5 with the OLS results confirming that the observed graphical results are statistically significant.

1.4.2 Regression Discontinuity Analysis

The main specification considers all students in grades 1 through 8 with 58% of all students in these grades being invited to participate and 96.8% of those students being invited due to having a below grade level score in math or reading. I conduct this analysis for all grade levels pooled together using recentered test scores which tell us how far a student's score is from their grade and subject combination. For each case, I use the student's lowest score in winter 2021, relative to the threshold, as the underlying variable given that being below grade level in just one subject would yield a student eligible. I repeat each analysis for the outcome variables of both math scores in fall 2021, shown in figure 1.6 and table 1.3, and reading scores in fall 2021, shown in figure 1.7 and table 1.4. The main analysis used a bandwidth that was determined to be optimal by the RDRobust code developed by Calonico et. al. (2017) in order to minimize bias[4].

[4] The code in Stata is rdrobust which calculates an optimal bandwidth and provides the coefficient on the on the invitation indicator term.

Figure 1.6. RDD Graphical Analysis of the Impact of Summer School Invitation Fall 2021 Math Scores

Table 1.3 RDD Estimates of the Impact of Summer School Invitation Fall 2021 Math Scores

	(1)	(2)	Elementary Grades Only (3)	Middle Grades Only (4)
Coefficient	-0.250	-0.564	-0.968	1.910
Standard Error	(0.599)	(0.617)	(0.749)	(1.428)
P > |z|	0.677	0.361	0.196	0.181
N	27,552	27,552	18,186	9,366
Prior (Fall 2020) Scores		X		

Notes. The main specification for these results uses a restricted sample of students who were invited to participate due to iReady scores and students who were not invited to participate due to iReady scores. A total of 14,108 students fall within the bandwidth of the analysis.

Figure 1.7. RDD Graphical Analysis of the Impact of Summer School Invitation Fall 2021 Reading Scores

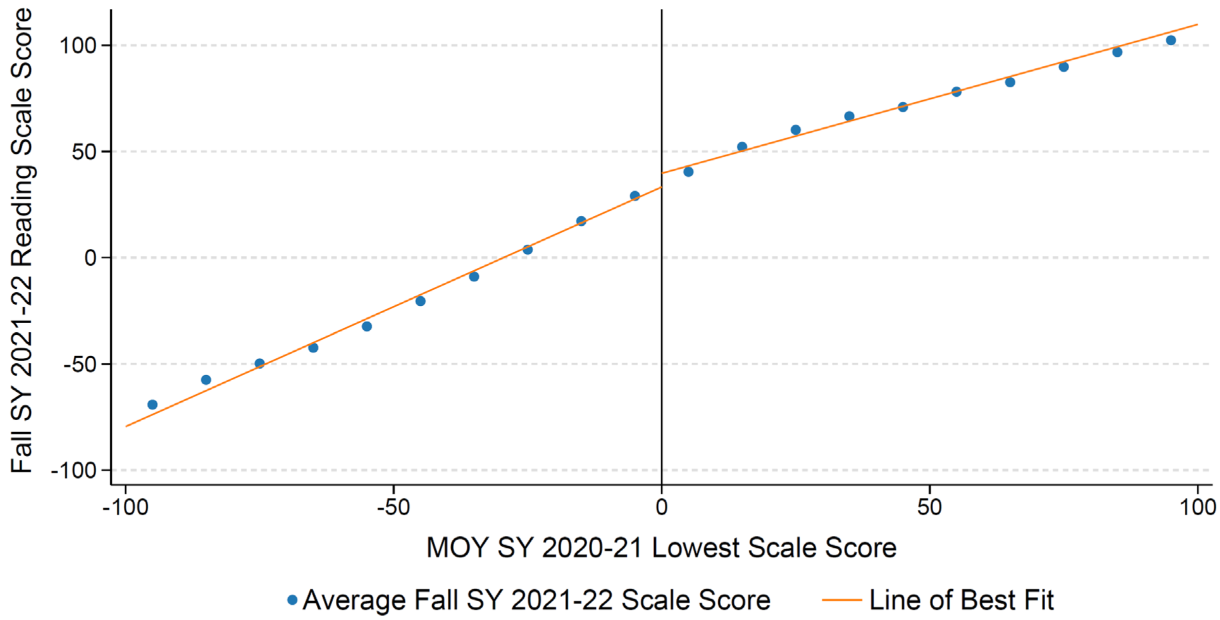


Table 1.4. RDD Estimates of the Impact of Summer School Invitation Fall 2021 Reading Scores

	(1)	(2)	Elementary Grades Only (3)	Middle Grades Only (4)
Coefficient	-1.405	-1.190	-1.852	2.282
Standard Error	(1.334)	(1.345)	(1.712)	(2.030)
P > |z|	0.292	0.376	0.279	0.261
N	31,163	31,163	18,024	9,211
Prior (Fall 2020) Scores		X		

Notes. The main specification for these results uses a restricted sample of students who were invited to participate due to iReady scores and students who were not invited to participate due to iReady scores. A total of 13,246 students fall within the bandwidth of the analysis.

For each analysis, I do not find impacts that are statistically significantly different from zero. I find that students who were invited to the program performed 0.25 scale points higher than noninvited counterparts in math and 1.41 scale points higher in reading, though neither of these estimates are statistically significant. Further, when controlling for prior test scores from the fall of the 2020-21 school year, shown in column (2) in each table, I continue to find insignificant results with attendees scoring 0.56 scale points higher in math and 1.19 scale points higher in reading than non-invitees. These results are also substantively insignificant as average expected growth for students is generally around 20-30 scale score points. Further, these null results are precise with a confidence interval of -0.26 to -0.24 in math and -1.42 to -1.39 in reading.

Finally, I conduct separate analyses for elementary and middle school students as prior studies have found differential impacts for the two levels, shown in columns (3) and (4). Invited students in elementary grades (1-5) scored 0.98 scale points higher in math and 1.85 scale points higher in reading than non-invitees in elementary grades while invited students in middle grades (6-8) scored 1.91 scale points lower in math and 2.28 scale points lower in reading than non-invitees, though none of these figures are significantly different from zero. In addition to the main analysis, I am interested in impacts on various subgroups. Therefore, I also conduct analyses which specifically include only Free or Reduced Price Meal (or non-FRPM) students, only English Language Learner (or non-ELL) students, only male or female, and only students in certain regions of the district, shown in table 1.5.

Table 1.5. RDD Estimates of the Impact of Summer School Invitation on Student Achievement in Fall 2021 (in Scale Score Points) by Subgroup

	Math	Reading
Male	0.558	-1.704
	(0.845)	(1.819)
Female	-1.471	-0.631
	(0.825)	(1.745)
FRPM-Eligible	1.772	-1.519
	(1.153)	(1.968)
Not FRPM-Eligible	-1.474	-2.129
	(0.756)	(1.704)
English Learner	-5.153	-0.197
	(5.055)	(6.125)
Not English Learner	-0.065	-1.338
	(0.600)	(1.342)
Higher-Income Region	-0.975	-1.192
	(0.811)	(1.960)
Lower-Income Region	-0.721	-3.507
	(1.544)	(3.080)

Notes. Standard errors in parentheses.

I am specifically interested in this to understand whether the program was effective at closing achievement gaps that have widened as a result of the pandemic. However, I do not find a significant difference for invitees and non-invitees in any student subgroup.

1.4.3 Validity Testing of the Results

The regression discontinuity design faces a few main threats to identification. Therefore, it is important to test for the validity of the main result. The first test that I conduct is a test for observed covariates. A regression discontinuity design assumes that observations are similar near the cutoff as assignment to treatment should be random at the threshold. This means that controlling for observed characteristics should not impact the results of the analysis. Thus, the test for observed covariates introduces observed characteristics including gender, FRPM status, English Learner status, and grade level to see if introducing these changes the results. I find that the introduction of observed covariates does not change our initial findings for either math or reading (see table A3). In addition to testing for observed covariates, I also test for balance of covariates. As I assume randomness at the threshold, I want to ensure that observed covariates are balanced at the cutoff. I conduct this test by running the RDD analysis using each covariate as the dependent variable. The covariates used in this test include FRPM eligibility, gender, English language learner status, race, and ethnicity. I find in each case that there is no difference in the share of students belonging to certain subgroups on each side of the invitation threshold (see table A4). Therefore, I believe that we have a balanced sample based on observed characteristics.

The second test that I conduct is a local polynomial density estimation to test for manipulation at the threshold, based on Cattaneo et.al. (2020). The manipulation test simply is checking for whether units assigned to treatment can manipulate their assignment by checking if there is a disproportionate number of students just above and below the threshold. In this case, I know intuitively that students could not alter whether they were above or below grade level on their iReady assessment and that they had no incentive to manipulate results given that the summer program had not been announced at the time of the assessment, invitation was not binding, and the test itself was not a high-states exam. However, I confirm with the test that there was no manipulation at the threshold as the density of students falling just above or just below is similar. While students could opt to attend or not attend the program, invitation to the program due to iReady scores appears to have not been impacted by student desires (see table A5). I also notice this visually with the distribution of math and reading scale scores being fairly normal with most of the density near the invitation threshold (see figures A1-A3).

1.4.4 Alternative Specifications

In addition to the main specification, I consider alternative specifications to test for robustness of the main result. First, I consider alternative bandwidths. The bandwidth is the specific area around the threshold which is used for the regression discontinuity analysis. For this test, I alter the bandwidths to see if a larger or smaller range of values impacts our results. I first consider larger bandwidths of 35 scale points for math and 30 scale points for reading. I then consider smaller bandwidths of 20 scale points for math and 15 scale points for reading. In each case, our results do not differ significantly from the original results (see table A6). The next alternative specification that I use to test for the robustness of the model is a polynomial ordering test. For the main analysis, I consider linear trends, or a polynomial of order 1, and an order of 2 for bias correction. For this test, I consider alternative polynomial orderings to ensure that our results are not sensitive to the order. I observe that none of the coefficients generated by this test are different from those found in the main results (see table A7).

Finally, I conduct placebo tests. As the threshold in this analysis is based on below iReady scores for grade and subject area combinations, I expect that any impact of the program would be noticed at that threshold. Further, I expect to not see jumps at other points in the distribution as there should be no other variations in assignment to treatment. Therefore, placebo testing ensures that the only source of variation is at the expected cutoff and thus considers the impact at placebo points. As the threshold used is at 0, I consider placebo cutoffs at -30 and +30 for both math and reading. I notice that none of the placebo thresholds yield a coefficient which is significantly different from zero which suggests that there is no other discontinuity in our distribution (see table A8).

1.5 Additional Analyses

1.5.1 Regression Discontinuity for Eligibility by Course Grades

While the main analysis of this study considers eligibility due to below iReady test scores, I also observe that many middle school students were deemed eligible due to failing course grades. Thus, I conduct a similar regression using students who were eligible due to failing course grades versus students who were not eligible at all and did not attend the program. I note that only 26 percent of invited middle school students were invited due to failing course grades, and only 4 percent of middle school students were invited *only* due to failing course grades and not some additional reason (see table A9). Thus, while I do present the results of this analysis in table 1.5, I acknowledge that the sample size for students invited to participate is very low, and that a very small number of students are added to our analysis by examining eligibility due to course grades. Our main specification excludes students who failed a course but were not invited and students who attended the program but did not fail a course.

Table 1.6. RDD Estimates of the Impact of Summer School Invitation on Student Achievement in Fall 2021 (in Scale Score Points) based on Invitation Due to Course Grades

	(1)	(2)
Math	14.068**	-8.828
	(4.651)	(4.196)
Reading/ELA	4.987	1.303
	(7.466)	(6.548)
Student Demographic Controls		X

Notes. Failing a math course led to an invitation to participate in math instruction, and thus should relate to future math scores. Likewise, failing an English-Language Arts (ELA) course led to an invitation to participate in reading/ELA/science/social studies instruction and thus should relate to future reading scores. Controls used include gender, FRPM eligibility status, and ELL status. Asterisks denote statistical significance, *** p<0.001, ** p<0.005, * p<0.01

I find that students who were invited to participate in the program due to failing a math course scored 14 scale points higher in math which is statistically significant. This figure grows to 16 scale points when including students who were previously excluded. However, I do not find impacts that are significantly different from zero when considering reading scores for students who failed an English-Language Arts course with invitees scoring 5 points lower than non-invitees and 5 points higher when considering the full sample (see table 16).

Given these results, I also consider the validity of this analysis. While the results are interesting, particularly for math, when I conduct the test for observed covariates (column (2)), the findings do not hold. That is, when I include observed covariates of gender, free or reduced-price meal status, and English-learner status into the model, the impacts for math become insignificantly different from zero. This suggests that, while there may be a correlation between invitation due to math grades and achievement, I cannot rule out the possibility that the impact I observed is in fact due to existing differences between the two groups of students.

1.5.2 Correlational Analyses

While the main analysis did not indicate that the program was effective for students near the threshold, I conduct correlational tests to understand if the program was related to student achievement at all. Interestingly, conditional on test scores on the winter assessments during the 2020-21 school year, invited students who attended scored 2.5 scale points lower in math and 6 scale points lower in reading than invitees who did not attend, with both figures being statistically significant. In addition, I evaluate whether attending the summer program for longer had any relationship to achievement as students in elementary grades could opt to attend just one or both sessions. I find that, conditional on winter test scores, students who attended both sessions did not perform significantly differently from students who only attended one session.

In a further attempt to understand the impact that this program may have had on widening achievement gaps, I perform correlational analyses on test scores at the beginning of the fall semester of the 2020-21 school year, conditional on winter of the 2020-21 school year, for students who attended the summer program by various subgroups, shown in table 1.4.

Table 1.7. Fall 2021 Sub-group Achievement Differences Conditional on Winter 2020 Achievement Levels by Summer School Participation

	Math			Reading		
Subgroup Comparison	Invited and Attended	Invited, Did Not Attend	Diff.	Invited and Attended	Invited, Did Not Attend	Diff.
Attendees vs. Non-Attendees	-2.461***			-6.207***		
Attended 2 Sessions vs. 1 Session	0.368 (1.037)			-0.068 (1.663)		
Female vs. Male	0.34 (0.83)	-0.42 (0.37)	0.76***	6.88*** (1.34)	1.22* (0.61)	5.67***
FRPM vs. non-FRPM	-6.64*** (1.04)	-8.54*** (0.38)	1.91***	-7.79*** (1.70)	-13.43*** (0.63)	5.64***
EL vs. non-EL	1.19 (1.01)	-2.12*** (0.62)	3.31***	-1.66 (1.62)	-5.13*** (0.99)	3.47***
Lower-Income vs. Higher-Income Region	-6.93*** (0.89)	-9.65*** (0.44)	2.72***	-6.60*** (1.43)	-13.88*** (0.73)	7.28***

Notes. Table shows impact of belonging to a given subgroup on fall 2021 test scores conditional on winter 2021 test scores for invited attendees and invited non-attendees. Parentheses denote standard errors. Asterisks denote statistical significance, *** p<0.001, ** p<0.005, * p<0.01

By conditioning on scores when the students were deemed eligible for summer school, our results tell us how achievement gaps changed for students based on whether they opted to attend or not. I also acknowledge that, given the literature on summer learning loss, widening of achievement gaps is expected so I are interested in how achievement gaps widened between attendees and non-attendees.

First, while achievement gaps for male and female students, where female students perform slightly better than male students, did not change after the summer program in math, I do observe that the gap grew about one scale point for attendees compared to non-attendees. Further, I observe that the gap grew for all students in reading but that the gap grew by about 6 scale points more for invited students who attended the program compared to those who did not attend. This suggests that the summer program is related to widened gender achievement gaps though it is uncertain whether that is due to differences in the students who opted to attend or the program itself. Next, I consider the gap between English learners and English speakers where English speakers perform better than English learners. The gap in both math and reading did not change significantly after the summer program for those students who attended, though it grew significantly for students who did not attend the program but were invited. Further, the gap grew about 3 scale points more in both math and reading for students who did not attend compared to students who did attend which suggests that the program may have mitigated the impacts of summer learning loss for those who attended.

Finally, I consider income-based achievement gaps by looking at both free or reduced-price meal eligibility and whether a student lives in the more or less affluent portion of the district. For both cases, the existing achievement gap had students from more affluent backgrounds performing better than students from less affluent backgrounds, so FRPM status and location both help us to proxy student socioeconomic status. Both measures suggest that achievement gaps grew in both math and reading after the summer program, which is expected due to previous literature on summer learning loss. However, I am more interested in how achievement gaps grew for students who participated in the program versus those who did not. When considering FRPM eligibility status, I observe that the achievement gap grew by about 2 scale points more in math and 6 scale points more in reading for invited students who did not attend the program compared to invited attendees. As for location, I observe that the gap grew about 3 scale points more in math and 7 scale points more in reading for invited non-attendees compared to invited attendees. This suggests that participation in the summer program is related to less growth in achievement gaps, though it is not certain whether this is due to unobserved differences in students who opted to attend or the program itself.

1.6 Discussion

In this chapter, I evaluate the impact of a summer school program in 2021 on student achievement in the following school year. This program was developed in response to lowered student achievement growth during the COVID-19 pandemic. I found the program to have minimal impacts on student test scores in both math and reading; I found this result to hold through multiple specifications and for all grade levels. While these results align with the literature regarding effectiveness in reading achievement, I do note that many studies do find impacts in math which are not observed in this study. These findings are likely due to the nature of the program in that it focused on generalized instruction and yielded low participation.

Further, I observe that the majority of students who took part in the program were deemed eligible for free or reduced-price meals. I also note existing achievement gaps as most FRPM-eligible students and most English Language Learning students in the district met the initial criteria for invitation to the program. Therefore, I explore impacts of the program on various groups of students but do not find the program to be effective in closing achievement gaps even among students who attended and found students from more advantaged backgrounds to fare better following the program. Therefore, our results reveal important implications not only for understanding summer school programs in general but also for how they can impact students from various backgrounds.

1.6.1 Limitations and Concerns

One main concern of this study is the lack of participation in the summer school program. As attendance was only recommended but not required of eligible students, many opted to not participate in the program. This leads to a relatively low sample size to work with, though the district is large enough that there is still a significant amount of students in the sample. Additionally, while all forms of non-compliance are important to consider, the number of students who attended but were not initially deemed as eligible is very low making the primary concern the never-takers. A second concern is a lack of density around the cutoffs for some grade and subject combinations which means that the RD analysis is not be as clean as hoped. While the iReady assessments are normed to have a normal distribution across all test takers, the grade and subject combinations for this district show that there is a decline in students receiving a certain score right around the below-grade-level threshold which shows in the breakdown of students who were eligible for and attended summer school.

A final concern of this study is that there were multiple eligibility criteria and that underlying data for some of these was not available. While I attempt to address this by restricting our sample to subgroups of students eligible by only certain criteria, we are left without the full picture of the impact of summer school on some students, particularly those on an adapted curriculum and students who attended based on a teacher recommendation but did not meet one of the formal eligibility criteria. I also acknowledge that using a regression discontinuity design does not yield generalizable results but rather suggests a certain effect for those near the cutoff (known as the "local area treatment effect" or LATE); that is, I am unable to conclude whether this summer school program was effective for all students but I am able to conclude whether it was effective for those students who were just below grade level.

1.6.2 Policy Implications

Given that this program had minimal impacts on student achievement, I argue that districts that wish to implement summer programs in the future consider a few elements for their programs. First, we know from the literature that programs that better target student needs are more effective at boosting student achievement. This program did not specifically target student needs in certain areas and therefore believe that districts should consider this when planning programs. Further, the literature is mixed on the efficacy of summer programs alone. Therefore, I believe that districts should consider alternative or complementary programs such as after school programs for improving student outcomes.

While most summer programs aim to target academic outcomes for students, I argue that summer programs can play alternative roles in student success. First, many authors have noted that summer programs can improve student social-emotional outcomes. Therefore, it may be worthwhile for districts to focus summer programs on non-academic outcomes. Further, as our program mainly served students from disadvantaged backgrounds, I believe that there is a need in this district for holistic services during the summer. Specifically, as the summer program provided meals, I theorize that this benefit may have been an important factor in families deciding to take advantage of the program.

Finally, as low participation is a common problem among summer programs, districts may consider alternative ways to entice students to participate such as through full-day programs which then solve a childcare problem, one that I believe families in our district may have faced due to higher participation among elementary-aged students. Further, programs with an element of “fun” such as camp-like activities, crafts, and games have been shown to have higher attendance and participation. Without giving greater incentives for students to attend, voluntary programs are unlikely to help students to “catch up” both in the context of the pandemic and beyond.

1.6.3 Conclusion

I use a regression discontinuity design to analyze a summer school program implemented in 2021 in response to the COVID-19 pandemic. I find that it did not have any meaningful impact on student achievement in the school year following the program. Further, I note that the program primarily served students from disadvantaged backgrounds but that the program did little to close achievement gaps which were widened during the pandemic. finally, this chapter discusses various ways for districts to utilize summer programs to better serve students such as targeting programs towards student needs, providing holistic benefits to students both within and outside of summer school, various methods for improving attendance at summer programs, and alternative remediation programs such as after school programs.

Chapter 2: Understanding Teacher Labor Markets in Metro-Atlanta during the COVID-19 Pandemic

2.1 Introduction

The COVID-19 pandemic impacted teachers in new and unexpected ways. In the spring semester of 2020, most schools across the country were forced to switch to remote learning with little preparation. For many districts, virtual learning continued into the following school year. This study is intended to analyze the impacts of the pandemic on teacher labor markets in two large school districts in the Southeastern United States. I aim to not only gain a better understanding of teacher labor markets in these districts in the context of the pandemic, but also determine appropriate policy interventions in response to teacher mobility and retention findings. The first goal of this study is to understand if and how the pandemic exacerbated existing teacher labor supply issues, including attrition, retention and mobility. The next goal is to analyze if the pandemic brought about new teacher labor supply challenges. The final goal is to examine how teacher labor markets during the pandemic compare to pre-pandemic markets to better understand long-run teacher labor supply. I hope to better guide teacher-focused policies in a post-pandemic world by understanding the impact of the pandemic on teachers.

2.1.1 Traditional Teacher Labor Supply Issues

There are a number of teacher labor supply issues that have been well-documented in the literature, including chronic shortages of teachers in areas such as math, science, special education, and difficulty in attracting and retaining teachers to serve students in schools with high rates of poverty, low average student achievement, and high proportions of underrepresented minorities. These labor supply issues can be traced to the invariance of wages across subject areas and schools within a district, combined with varying opportunity costs. The opportunity cost of teaching for potential math and science teachers is much higher than that for teachers in other subject areas (Macdonald, 1999; Ingersoll, 2007; Feng & Sass, 2018; Sutcher et. al., 2019; See et. al., 2020). Another subject area that has seen difficulties, particularly with recruitment but also attrition, is special education (SPED). SPED teachers may face challenges with student behavioral issues and increased paperwork associated with crafting and implementing individualized education plans for their students. Consequently, many view the job as unappealing and difficult (Pyecha et. al., 1995; Macdonald, 1999; Sutcher et. al., 2019). Finally, shortages have been noted for English as a Second Language (ESL) teachers (Sutcher et. al., 2019)

In addition, teacher mobility is related to student characteristics. Numerous studies have shown that schools with more low-income students and more minority students tend to have a harder time with hiring and retention, with characteristics of students in a teacher's individual classroom playing a larger role than student characteristics in the school as a whole (Hanushek et. al., 2004; Scafidi, 2007; Feng, 2009; Sutcher et. al., 2019). Studies have also found that student achievement matters with low-performing schools having more problems with retention which leads to the lowest performing students often being taught by the least qualified teachers as they often have early-career teachers who transfer schools when able (Boyd et. al., 2005; Falch & Rønning, 2007; Scafidi, 2007). However, school and occupational factors also influence teacher hiring and retention and these may have more of an impact than student characteristics. Specifically, low salaries and working conditions including poor facilities, lack of materials, and student behavior, and lack of administrative support have been shown to be some of the biggest influences in teacher retention in a given school and in the profession itself (Hanushek et. al., 2004; Loeb et. al., 2005; Ingersoll, 2007).

Finally, teacher characteristics are also related to teacher recruitment and retention. Particularly, teachers of color are underrepresented in US public schools (Carter Andrews et. al., 2019; Farinde-Wu et. al., 2020). In addition, racial and ethnicity matching of teachers, peers, and administrators has been found to be an important factor for reducing teacher turnover, particularly for black teachers (Rodriguez et. al., 2022). While there have been efforts in recent years to improve recruitment of teachers of color into the profession, there remain issues in retaining teachers due to challenges in the workplace (Cochran-Smith, 2004; Farinde-Wu et. al., 2020). Considering the impact of teacher race on teacher labor markets is particularly important, as racial matching of teachers and students has benefits for students and can be particularly important in improving outcomes for minoritized students (Carter Andrews et. al., 2019; Farinde-Wu et. al., 2020).

2.1.2 Teacher Labor Supply Issues during COVID-19

While teacher labor supply was a topic of interest pre-pandemic, this paper also considers new issues that may have arisen as a result of the pandemic. The Bureau of Labor Statistics (BLS) reported a decline in the K-12 labor force at the start of the COVID-19 pandemic with current employment levels still below pre-pandemic levels, and numerous states have reported difficulties with filling vacancies in the 2021-22 school year (Bleiberg & Kraft, 2022). During the COVID-19 pandemic, many teachers reported difficulties with balancing home and work life (Walker et. al., 2020; Kraft et. al., 2021). In addition, many teachers have said that the transition to virtual learning presented a new hardship, as many felt that they did not have adequate resources to be successful and that engaging with students and parents was made much more difficult (Fauzi & Sastra Khusuma, 2020; Walker et. al., 2020; Lei & So, 2021; Zamarro et. al., 2022). In general, the pandemic led to increased stress and burnout of teachers. Support from administration was the most important factor that influenced teacher satisfaction during the pandemic, though most teachers cited peers as being their main source of support (Walker et. al., 2020; Eadie et. al., 2021; Kraft et. al., 2021; Walter & Fox, 2021; Zamarro et. al., 2022).

The pandemic also heightened the importance of other teacher labor concerns, such as differences in retention by age and experience. Very few teachers in the US ever make it to full retirement (Macdonald, 1999). Numerous studies have documented that teachers are most likely to leave teaching in the first five years, with those with a greater intrinsic motivation for teaching being more likely to stay (Fantilli & McDougall, 2009; Van den Borre et. al., 2021). Higher quality teachers are less likely to retire, conditional on age and experience, but attrition in general increases during a teacher's last few years before reaching retirement age (Macdonald, 1999; Ni et. al., 2022). While age and experience are important to consider in general, they are especially important in the COVID-19 context, as crisis teaching not only may have placed additional hardships on early career teachers, but the increased use of technology may have placed a unique hardship on older teachers.

One additional area that the pandemic has brought to light is policy regarding substitute teachers. While shortages of substitute teachers were known pre-pandemic, these shortages were made worse with the onset of COVID-19 and were an important reason that many schools had to close at various points during the pandemic as schools were unable to staff classes. While demand for substitute teachers was lower at the start of the pandemic in spring 2020 and the start of fall 2020, when most schools were fully virtual, many districts experienced an even lower supply of substitute teachers as schools began to reopen (Giffin et. al., 2021). Existing substitute teacher supply problems were made worse by the higher demand for substitute teachers given more teacher absences; however, the pandemic also presented substitute teachers with new factors to consider, particularly new health concerns, especially given that many substitute teachers are retired teachers and therefore older and at a higher health risk. In addition, there were childcare concerns as schools were forced to close, and many substitute teachers are parents of school-age children (Saenz-Armstrong, 2020; Will, 2020). While substitute teachers are an area of interest during the pandemic, there is not much research that has been done on the topic, though the limited research has suggested that substitute teacher job decisions have historically been made based on school and job characteristics (Gershenson, 2012).

2.1.3 Teacher Labor Supply Policy

As this paper intends to provide information regarding teacher labor supply, it is important to consider policy options for addressing any potential teacher retention and mobility concerns. Many teachers report that higher salaries would help to keep them in the profession. Consequently, many districts have employed differential salary programs, bonus programs, and loan forgiveness programs in hopes of retaining teachers (Schwartz, 2021). While salary increases and loan forgiveness programs appear to be effective at retaining teachers in the profession, there is mixed evidence on the efficacy of bonus programs on the retention of teachers, though they do help with attracting teachers to the profession (Clotfelter, 2008; Feng, 2009; Feng & Sass, 2018; See et. al., 2020). In addition to looking at financial mechanisms to recruit and retain teachers, studies have examined the impact of other programs which target teacher satisfaction and have found generally positive impacts for initiatives such as mentoring programs, continuing education programs, and increased administrative support and collaboration (See et. al., 2020; Van der Vyver et. al., 2020; Whitfield et. al., 2021).

2.1.4 The Current Study

This study is primarily descriptive, providing a multivariate analysis of various factors that are correlated with teacher retention and mobility. The first research question is how did the pandemic impact traditional teacher labor issues such as difficulties in hiring and retaining teachers in certain subjects and at schools with certain student characteristics? The second main research question is what new teacher labor supply issues arose from the pandemic itself? For instance, there may be age and experience differences in retention and mobility, particularly with newer teachers being less likely to persevere, older teachers leaving the profession due to discomforts with technology, or more experienced teachers choosing to persevere in an effort to reach retirement. Answering these questions helps us to understand how the composition of exiting teachers changed during the pandemic.

It is important to note that, while the main analysis focuses on teacher retention within a position at a given school, I also analyze teacher mobility to understand which teachers transfer schools, which teachers change positions within a school or district, and which teachers transfer to teach in other school districts in the state. In addition, as the study includes multiple districts, I examine the districts separately, but also to compare results across the two districts. This analysis is particularly useful for helping districts navigate the current pandemic circumstances while also guiding policy on future use of virtual learning as it impacts teachers and for understanding potential long-term effects of the pandemic.

2.2. Methodology

2.2.1 Data and Context

This project utilizes data from two large, diverse school districts in the Southeast United States. The districts, denoted as District A and District B for anonymity, provided data on student performance, student sociodemographic characteristics, teacher employment, and teacher sociodemographic characteristics. Sociodemographic characteristics that are tracked by the district include gender, race, ethnicity, Free or Reduced-Price Meal (FRPM) status (a crude measure of student household income), disability status, and English Language Learner (ELL) status. It is important to note that, while both districts provided teacher employment data, neither provided information on vacancies. That is, while I observe the number of active and teachers in each period, I do not observe the number of job openings in the district, so I cannot determine the extent of any teacher shortages. Further, I cannot reliably determine the extent to which long-term substitutes or other non-certified instructional personnel are temporarily providing classroom instruction. Therefore, this study only considers teachers who are certified to teach and whose job assignment is as a teacher.

The teacher employment data include all active teachers in a given year. In addition, the data include information on teachers who leave the district in the semester immediately following their last active semester. In district A, all teachers who leave the district are reported as having resigned or died. In district B, I have detailed information on the stated reasons for teacher departures which include resignation, retirement, acceptance of a teaching position in another district in Georgia, death, family (including personal illness), advanced study, nonrenewal of contract, reduction in force, and failure to meet certification requirements. Given that teacher departures were not perfectly reported or given the possibility of a teacher moving to a non-instructional position, the attrition rate that I calculate is the number of teachers who taught in the spring of the given year who do not return to teach in the district in the following year, expressed as a percentage of active teachers in the given year. However, I use specific departure reasons in District B for some analyses. I also have access to data on the school that a teacher works in and can track which teachers change schools within a district or teach in multiple schools in the district.

As with most schools in the United States, both districts of interest were forced to close their physical schools in the spring 2020 semester due to the COVID-19 virus. Both began the 2020-21 school year virtually but reopened school buildings later in the school year, with District A reopening during the fall semester for students who opted to return in-person and District B reopening during the spring 2021 semester for those who opted to return to face-to-face learning. Additionally, both districts allowed families to choose virtual or face-to-face learning in the 2021-22 school year. However, both districts had to close schools at different times due to local infection rates and staffing shortages.

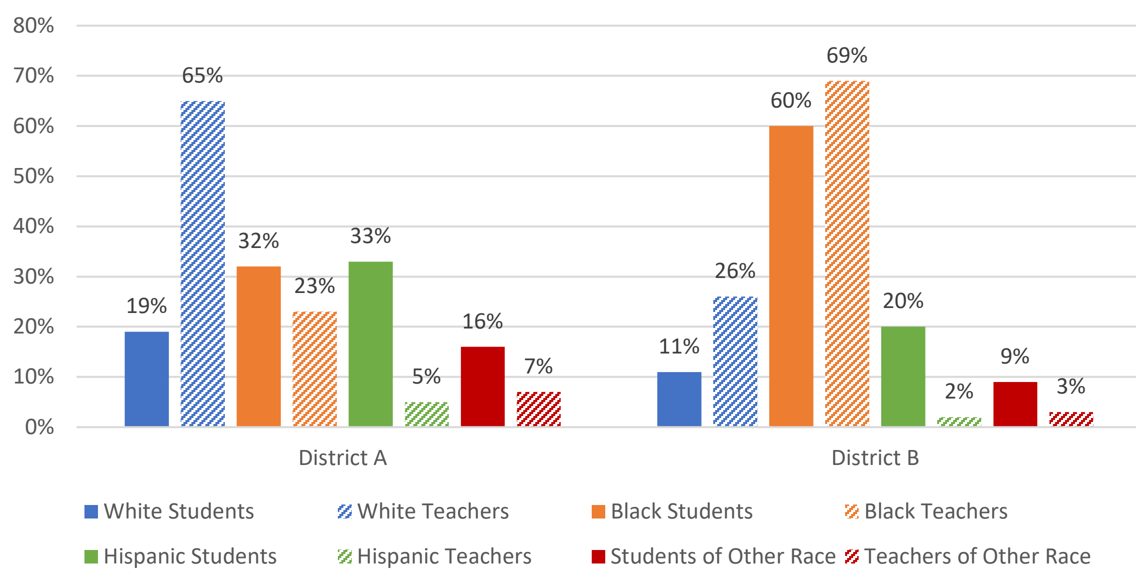
The two districts of interest also implemented teacher incentive programs for recruiting and retaining teachers. District A provided a bonus to new teachers in the 2020-21 or 2021-22 school year who signed a contract for the following year. The bonus amount differed based on subject area with amounts ranging from $3,000 for general teachers to $6,000 for some special education teachers[5]. District B implemented both a new hire supplement of $2,000 and, for existing teachers, a two-time retention supplement of 3% of a teacher's existing salary. In addition to the recruitment and retention incentives, both districts gave incentives starting at $350 in District A and $200 in District B for referring others who sign a contract to work in the

[5] New hire bonuses in District A differed by subject area. The general teacher incentive was $3,000 in non-Title 1 schools and $4,000 in Title 1 schools. Teachers in math, science, computer science, and engineering as well as bilingual teachers also received $4,000. The bonus for special education teachers started at $5,000 and increased to $6,000 for teachers in "severe" programs and for speech language pathology teachers. Teachers who qualified for multiple incentives would receive the one with the highest dollar amount.

district[6]. Finally, both districts implemented pandemic-related incentives including bonuses for receiving the COVID-19 vaccine ($500 in District A and $1,000 in District B) and, in District B, a bonus of $3,500 for teachers who signed an agreement to concurrently teach students both in-person and virtually.

Both school districts of interest are large, diverse urban/suburban school districts in the metro-Atlanta area, though the two districts differ considerably in the students they serve. Figure 2.1 shows the breakdown of student and teacher races and ethnicities in both districts.

Figure 2.1. Racial and Ethnic Composition of Students and Teachers, SY 2021-22



In District A, Black and Hispanic students each make up about one-third of students in the district with approximately 35% of all students in the district qualifying for free or reduced-price

[6] District A's referral bonus per new teacher varied based on the subject area of the referred teacher. Referring a special education teacher resulted in a bonus of $450, referring a speech language pathology teacher resulted in a bonus of $500, and referring a teacher in any other subject area resulted in a bonus of $350. These bonuses were given after a new teacher had worked for 60 days. District B just had one bonus amount of $200 per referral and bonuses were given in the middle of the school year.

meals. However, in District B, about 60% of students are Black and about 70% qualify for free or reduced-price meals. While the majority of students in District A are from historically marginalized racial and ethnic groups, the majority of teachers in the district are White. In contrast, in District B, both the majority of students and the majority of teachers are Black. The teacher workforce in both districts is primarily female; 80% of teachers in District A and 77% of teachers in District B identify as female. Finally, I observe teacher experience (determined as the number of years a teacher has taught in any district) with 41% of teachers in District A and 42% of teachers in District B having less than 10 years of experience.

2.2.2 Empirical Method

I first conduct a descriptive analysis, presenting summary statistics on retention and mobility of teachers across schools and subject areas. This illustrates which subject areas currently have the greatest problems with retention, relative to the pre-COVID period. The analysis also describes the relationship between age, experience, having to teach virtually, and teacher retention and mobility.

To analyze the correlates of teacher attrition and mobility more rigorously, I also estimate binary logistic regression models of the following form:

$$ln(\frac{pr(y_{it})}{1-pr(y_{it})}) = X_{it}\beta + \alpha_s + \epsilon_{it}$$

where $pr(y_{it})$ is the probability that a teacher *i* in school year *t* does not return to teach in the given district in school year $t+1$; *X* is a vector of covariates for a certain teacher such as race/ethnicity, gender, or subject area; α_s is a time-invariant school effect for school s, and ϵ is the error term. This model is estimated using a maximum likelihood estimation method for three time periods: the beginning of school year 2016-17 school year through the start of the 2019-20 school year, described here as the “pre-pandemic” period; the period following the 2019-20 school year which is the time when the pandemic-related school closures first occurred; and the period following the 2020-21 school year which included pandemic-related virtual and hybrid learning in both districts.. While the binomial logistic regression provides insight into teacher attrition, I am also interested in teacher mobility within and outside of a given school district. Thus, I estimate the following multinomial logistic model (Engel, 1988) for the same three periods:

$$ln(\frac{pr\big(f(k,i,t)\big)}{1-pr(f(k,i,t))}) = X_{it}\beta + \alpha_s + \epsilon_{it}$$

where $pr\big(f(k,i,t)\big)$ is the probability that a teacher i in school year t makes a certain mobility decision, k, with decisions including to stay in the same position, change schools in a district, change districts (only in District B which provided detailed information on the reasons that teachers exit the district), or exit teaching all together[7]; X is a vector of covariates for a certain teacher such as race, gender, or subject area; a_s is the time invariant school effect for school s, and ϵ is the error term. Similar models are estimated using maximum likelihood estimation to measure impacts for certain school and position types.

I specifically consider teacher race and ethnicity, teacher gender, teacher experience level, subject area taught, and grade level (defined as elementary or middle/high). I choose these descriptive variables as they are either common ways to describe teacher characteristics or they represent groups that historically have higher attrition rates (particularly teacher experience and subject area). The racial and ethnic groups considered include Black teachers, Hispanic teachers,

[7] In District A, the decision to exit teaching refers to the decision of a teacher to not return to teach in the district. In District B, the decision to exit teaching refers to the decision of a teacher to not return to teach in a Georgia public school.

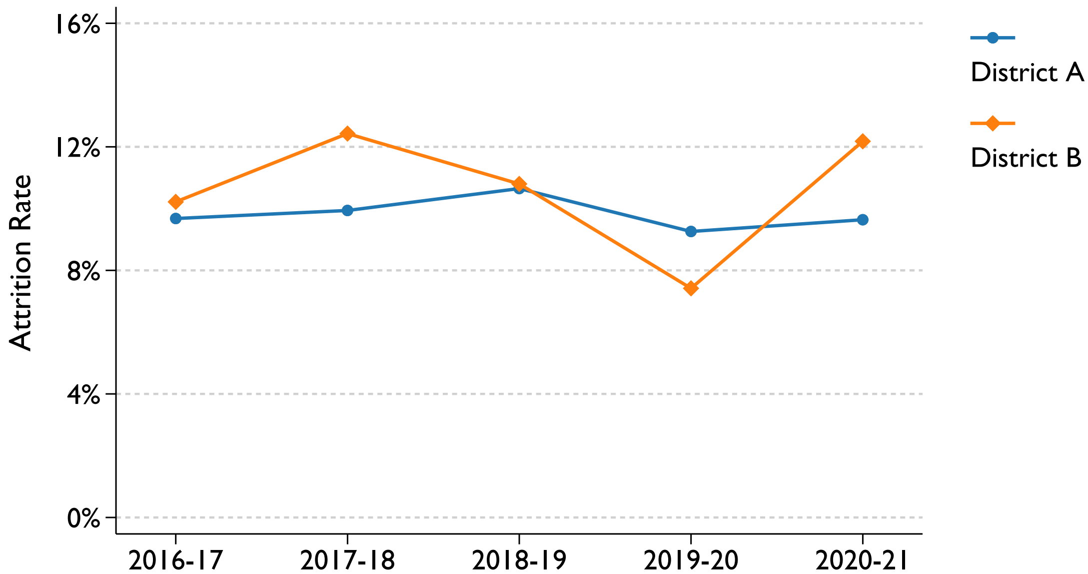
and teachers who identify as some other race with White teachers serving as the reference group. The subject areas considered include STEM subjects (science, technology, engineering, and math), foreign languages (including world languages and English as a second language), and special education, with teachers in lower-need subject areas in the reference group. I run each model with and without school fixed effects to consider overall trends in the district and to account for differences within particular schools. School fixed effects control for the particular school that a teacher works in, thereby holding constant all time-invariant differences across schools, such as the quality of school leaders and the demographic makeup of the student body. Therefore, the results with school fixed effects allow me to make comparisons within schools while the results without school fixed effects allow for comparisons across schools within the district. For the specifications without school fixed effects I include school-level characteristics that have been shown to impact teacher mobility including the percentage of students in a school that qualify for free or reduced price meals and the percentage of students in the school who identify as being non-white.

2.3. Results

2.3.1 Descriptive Results for Teacher Attrition and Hiring

Teacher attrition patterns over time are depicted for both districts in Figure 2.2

Figure 2.2. Teacher Attrition by District, SY 2016-17 to SY 2020-21



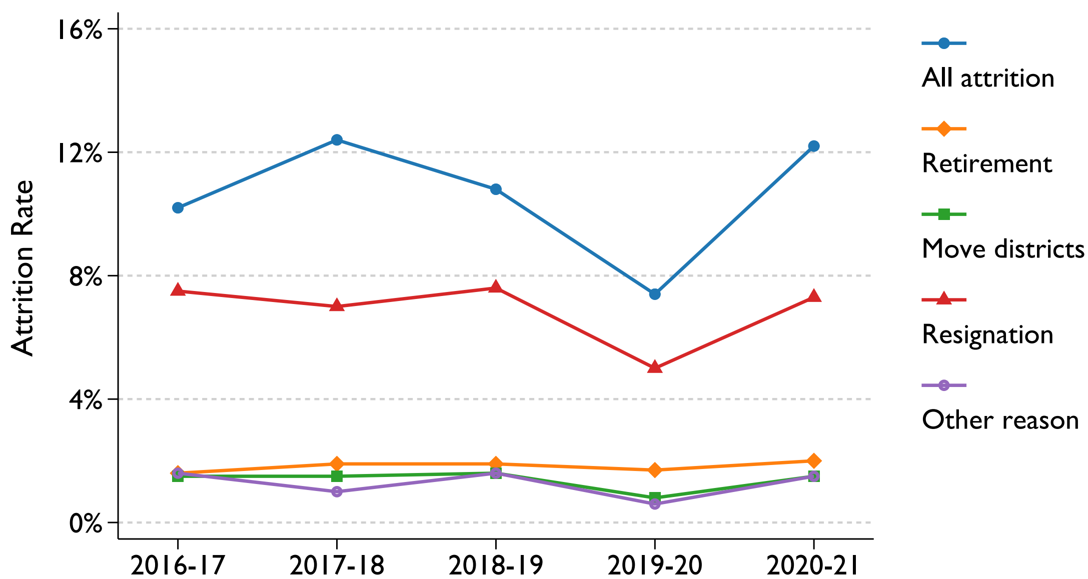
Notes. The attrition rate is the number of teachers who taught in the spring of the given year who do not return to teach in the district in the following year, expressed as a percentage of active teachers in the given year.

Prior to the pandemic, attrition was more variable in District A, with annual rates varying from 10.2 to 12.4 percent, than in District B, where attrition rates varied between 9.9 and 10.7 percent. At the end of the last pre-pandemic year, SY 2018-19, teacher attrition rates in the two districts were nearly identical, 10.8 percent in District A and 10.7 percent in District B. At the end of SY 2019-20, about 9 weeks after schools closed, teacher attrition rates in both districts fell, with a larger drop in District B than in District A. The decline in attrition is consistent with worsening employment prospects outside of education and greater labor market uncertainty as unemployment rates quickly rose in spring/summer of 2020. Consistent with improving labor market opportunities in 2021, attrition rates rose in both districts at the end of SY 2020-21. In each district, teacher attrition at the end of SY 2020-21 was equivalent to the rate at the end of SY 2017-18. In comparison to the last pre-pandemic year, SY 2020-21 attrition rates in District

A were higher than in SY 2018-19 and attrition rates in District B were lower than they were in SY 2018-19.

Given that District B provided detailed information on the stated reasons for teacher departures, I separately track resignations, retirements, acceptance of a teaching position in another district in Georgia, and other reasons for teacher exit in each year. Figure 2.3 displays the trends in teacher attrition over time, by reason, for teachers in District B.

Figure 2.3. Teacher Attrition by Reason in District B, SY 2016-17 to SY 2020-21



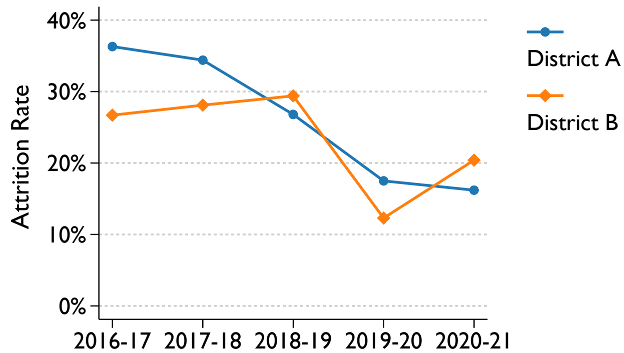
Notes. The attrition rate is the number of teachers who taught in the spring of the given year who do not return to teach in the district in the following year, expressed as a percentage of active teachers in the given year. "Other reasons" include death, family (including personal illness), advanced study, nonrenewal of contract, reduction in force, and failure to meet certification requirements.

The pattern of attrition rates for each reason type mirror that of overall attrition. However, while the year-to-year changes were substantial for most stated exit reasons, the change in retirement rates were almost imperceptible, moving from 1.8 percent in 2018-19 to 1.7 percent in 2019-20 and rising slightly to 2.0 percent at the end of SY 2020-21.

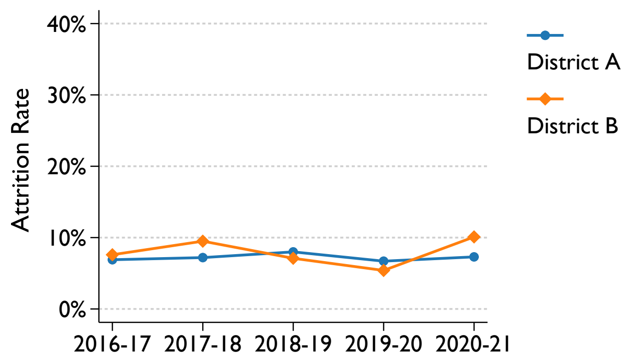
I also consider differences in attrition by teacher experience. Given the lack of data on the reasons for exit from District A, the attrition rate of teachers with high levels of experience can shed light on the impact of the pandemic on teacher retirement in District A. Further, as experienced teachers who retire or otherwise leave teaching are likely replaced by teachers with less experience, understanding attrition trends by experience level has important implications for understanding the quality of education that students may be receiving. Panel A of Figure 2.4 illustrates changes over time in teacher attrition for early-career teachers (0-4 years of experience), while panels B-C of Figure 4 map out changes over time in attrition rates for mid-career teachers (5-29 years of experience) and late-career teachers (30 or more years of experience), respectively.

Figure 2.4. Teacher Attrition by Years of Experience, SY 2016-17 to SY 2020-21

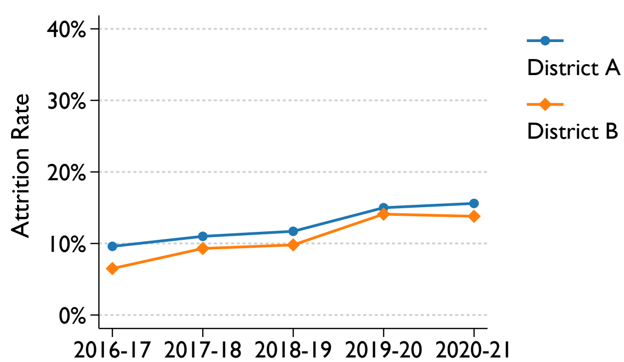
Panel A. Less than five years of experience



Panel B. Five-to-29 years of experience



Panel C. 30 or more years of experience



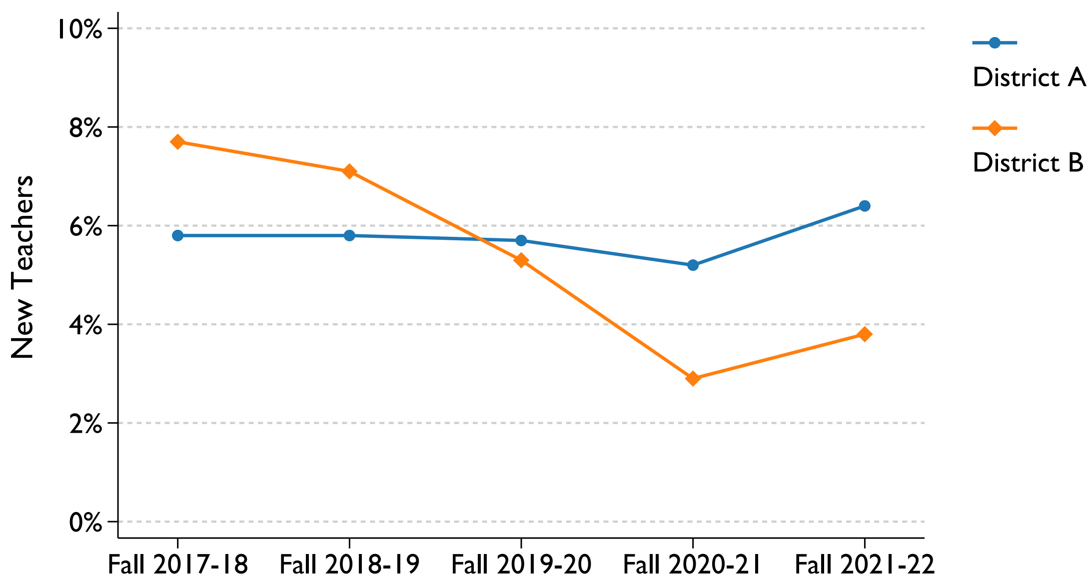
Notes. The attrition rate in panel A is the number of teachers with less than five years of experience who taught in the spring of the given year and who do not return to teach in the district in the following year, expressed as a percentage of active teachers with less than five years of experience in the given year. The attrition rate in panel B and panel C are the same except replacing less than five years of experience with five-to-29 years of experience and 30 or more years of experience, respectively.

Historically, attrition among early-career teachers is high throughout the U.S. and I observe that in Districts A and B as well. Prior to the pandemic, attrition for early-career teachers was on a downward trend, but remained high, ranging from 36.3 percent in SY 2016-17 to 26.8 percent at the end of SY 2018-19. In contrast, early-career teacher attrition was on an upward trend in District B prior to the pandemic, moving from 26.7 percent in SY 2016-17 to 29.4 percent in SY 2018-19. For district A, the proportion of early career teachers who leave has continued to decline throughout the pandemic, dropping from 26.8 percent in SY 2018-19 to 16.2 percent after SY 2020-21. In contrast, the attrition rate for early-career teachers in District B follows the same pattern as for all teachers. Attrition rates fell from 29.4 percent in SY 2018-19 to 12.3 percent in SY 2019-20 and then rebounded to 20.4 percent at the end of SY 2020-21. This is still well below the pre-pandemic attrition rate, meaning that early-career teachers in District B are less likely to leave teaching compared to pre-pandemic levels.

For mid-career teachers, attrition rates are relatively low, ranging from about 7 and one-half to 10 percent (panel B of Figure 4). In District A, attrition of mid-career teachers has been relatively flat over time, ranging from 6.7 to 8 percent over the SY 2016-17 to SY 2020-21 period. There has been a bit more variation in attrition rates of mid-career teachers in District B, with a decline from 7.0 in SY 2018-19 to 5.4 in SY 2019-20 and then a rebound to 10.1 percent in SY 2020-21. Panel C of Figure 4 displays attrition trends among the most experienced teachers, those with 30 or more years of experience. This is the experience level for teachers to receive full retirement pay under the traditional defined-benefit system in Georgia. In both districts, I observe a general upward trend over time in attrition rates for late-career teachers, with a diminished rate of growth (District A) or slight decline (District B) between SY 2019-20 and SY 2020-21. Consistent with the previous results on teacher retirements, this suggests that the pandemic did not lead to massive departures of highly experienced teachers from either District A or District B.

While understanding teacher attrition is important, I also consider trends in teacher hiring before and during the pandemic era. Figure 2.5 illustrates the trends in new teachers over time in both districts.

Figure 2.5. Proportion of New Teachers by District, Fall SY 2017-18 to Fall SY 2021-22

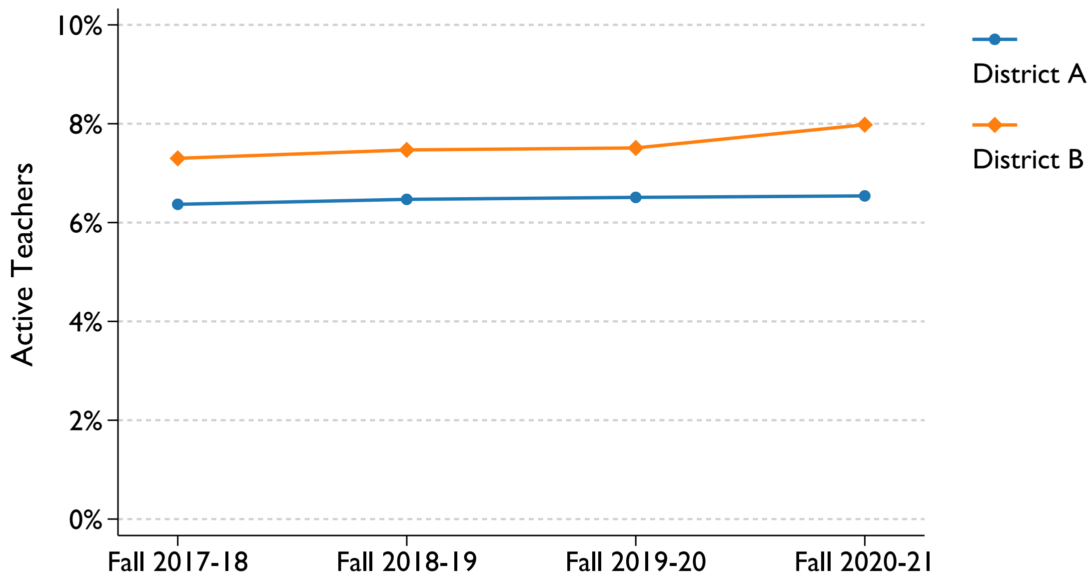


Notes. The proportion of new teachers in each year equals the number of new teachers as a percentage of active teachers in the given year.

I define new teachers as teachers who were not employed by the district in the previous school year. Thus, new teachers can include both those new to the profession as well as more experienced teachers who have transferred from another district. The proportion of teachers in District A who were new to their district was relatively constant at just under 6 percent prior to the pandemic, while District B experienced a decline in the proportion of new teachers in the pre-pandemic period. Consistent with trends in teacher attrition described above, both districts experienced a slight decline in the proportion of new teachers in Fall of SY 2020-21 (relative to pre-pandemic trends) and then a sharp increase in Fall of SY 2021-22. However, the proportion of new teachers in District B remained well below pre-pandemic levels and was higher than pre-pandemic levels in District A.

The hiring of new teachers may be due to the need to fill positions vacated by exiting teachers or it could be a result of the need to increase the number of teachers to meet increases in student enrollment. If the addition of new teachers does not cover both teacher attrition and enrollment increases, student-teacher ratios would rise, potentially harming student achievement. To estimate the net impacts of teacher attrition, changes in student enrollment and hiring of new teachers, in Figure 2.6 I plot the number of active teachers in each district as a percentage of students enrolled in the district in the fall of the given year.

Figure 2.6. Active Teachers as a Percentage of Enrolled Students, Fall SY 2017-18 to Fall SY 2020-21

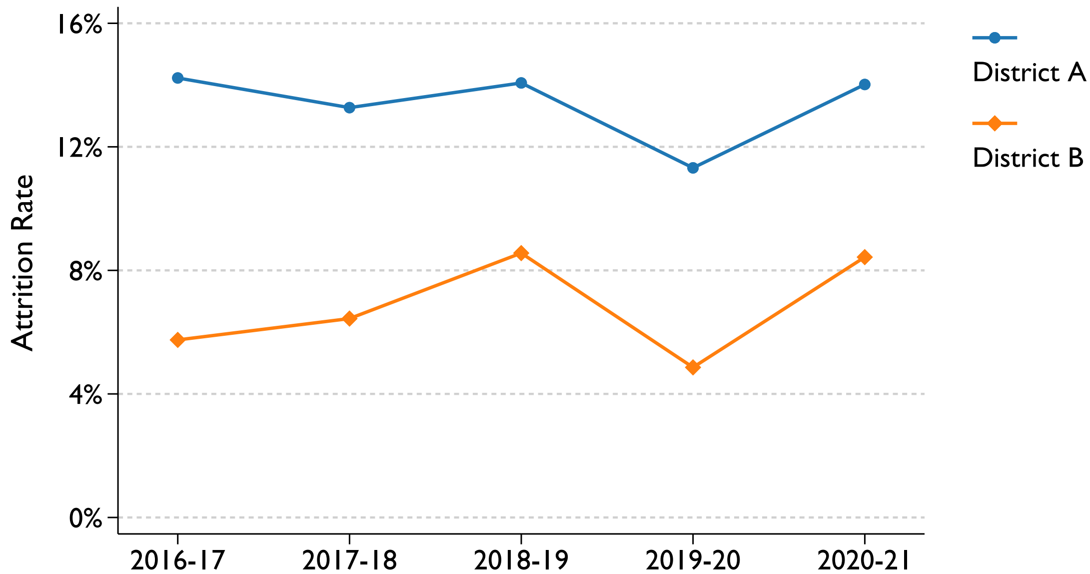


Notes. The proportion of active teachers in each year equals the number of active teachers as a percentage of enrolled students in the given year.

In both districts, the proportion of teachers remains relatively constant over time. This suggests that, on average, class sizes have not risen as a result of labor market changes during the pandemic.

Finally, I consider teacher labor market trends in hard-to-staff subject areas. Figure 2.7 illustrates special education teacher attrition trends in both District A and District B.

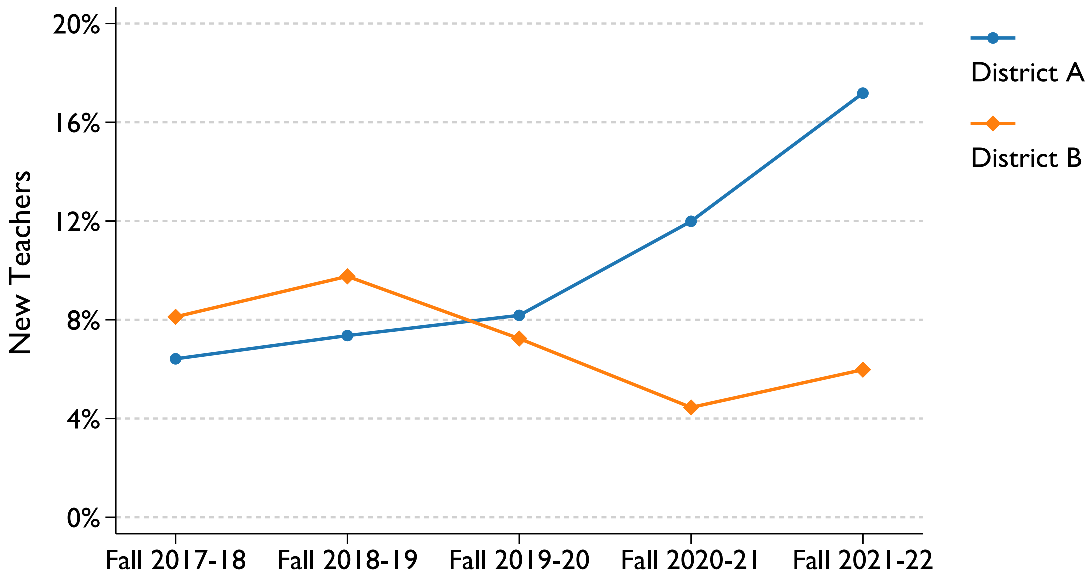
Figure 2.7. Attrition Rate for Special Education Teachers, SY 2016-17 to SY 2020-21



Notes. The attrition rate is the number of special education teachers who taught in the spring of the given year who do not return to teach in the district in the following year, expressed as a percentage of active special education teachers in the given year.

The two districts exhibit very similar patterns over time, though attrition of special education teachers is consistently 6-8 percentage points higher in District A. In both Districts there was an uptick in attrition from SY 2017-18 to SY 2018-19, followed by a sharp decline from SY 2018-19 to SY 2019-20 and then a substantial increase in SY 2020-21 as the general unemployment rate declined during the pandemic. The attrition levels in SY 2020-21 are nearly identical to those in each district in the year prior to the pandemic, SY 2018-19. While attrition patterns for special education teachers were similar across the two districts, there were stark differences in the within-districts changes in the proportion of new-to-the-district special education teachers over time, as illustrated in Figure 2.8.

Figure 2.8. Share of New Special Education Teachers, Fall SY 2017-18 to Fall SY 2021-22

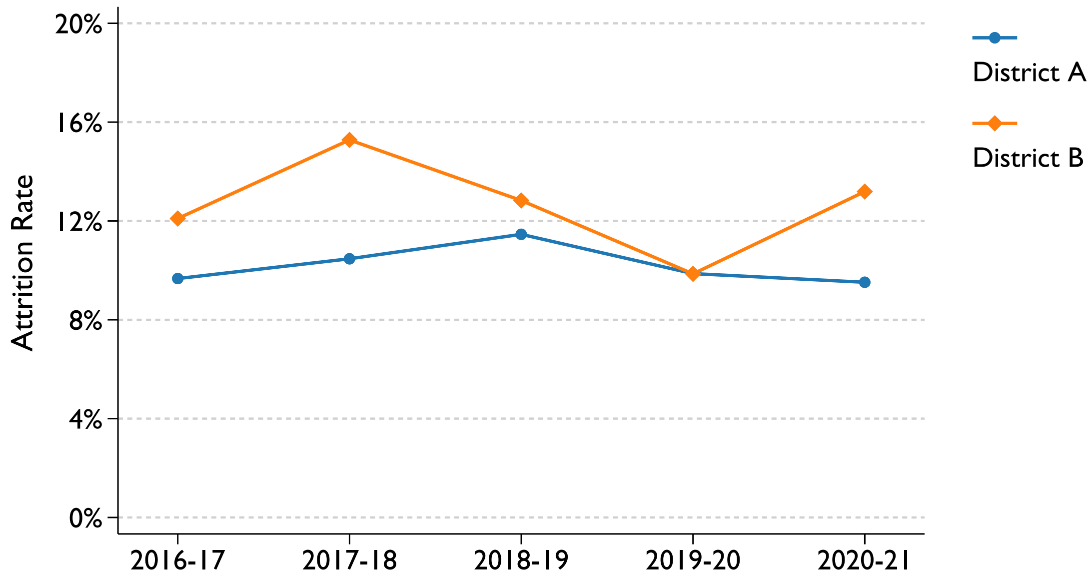


Notes. The share of new special education teachers equals the special education teachers who are new to teaching in the district as a percentage of active special education teachers in each year.

In District A, prior to the pandemic, the proportion of new hires was rising slowly over time. However, after the pandemic began, the proportion of new hires among special education teachers has skyrocketed, going from 8.2 percent in Fall of SY 2019-20 to 17.2 percent in Fall of SY 2021-22. In contrast, District B had a similar proportion of new-to-the-district special education teachers in Fall of SY 2019-20 (7.2 percent), but the share fell to 6.0 percent in Fall of SY 2021-22.

Figure 2.9 shows attrition trends among math and science teachers.

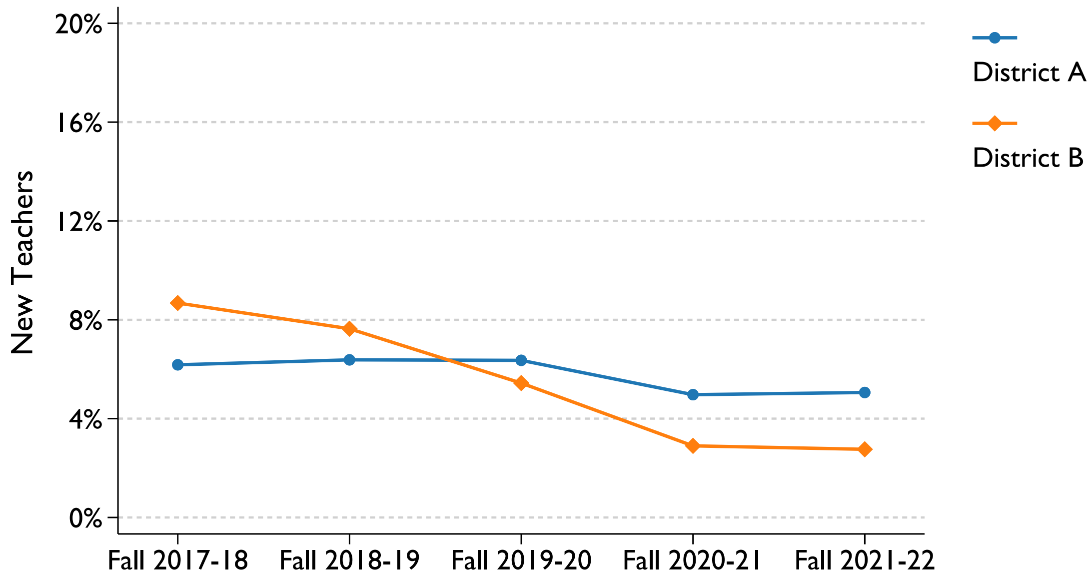
Figure 2.9. Attrition Rate for Math and Science Teachers, SY 2016-17 to SY 2020-21



Notes. The attrition rate is the number of math and science teachers who taught in the spring of the given year who do not return to teach in the district in the following year, expressed as a percentage of active math and science teachers in the given year.

In the pre-pandemic period, SY 2016-17 through SY 2018-19, attrition rates were higher in District B, where they ranged from 12 to 15 percent, compared to District A, where attrition of math and science teachers varied between 10 and 11 percent. For both districts, attrition rates fell near the beginning of the pandemic, equaling 10 percent in both districts. As the pandemic progressed and labor markets in general improved, attrition rates continued to decline slightly in District A, but rose precipitously in District B to a level of 13.2 percent in SY 2020-21. Despite the fact that attrition among math and science teachers has either increased during the pandemic (District B) or shown only a modest decline (District A), it appears that the proportion of math and science teachers that are new to the district has declined substantially during the pandemic in both districts, as shown in Figure 2.10.

Figure 2.10. Share of New Math and Science Teachers, Fall SY 2017-18 to Fall SY 2021-22

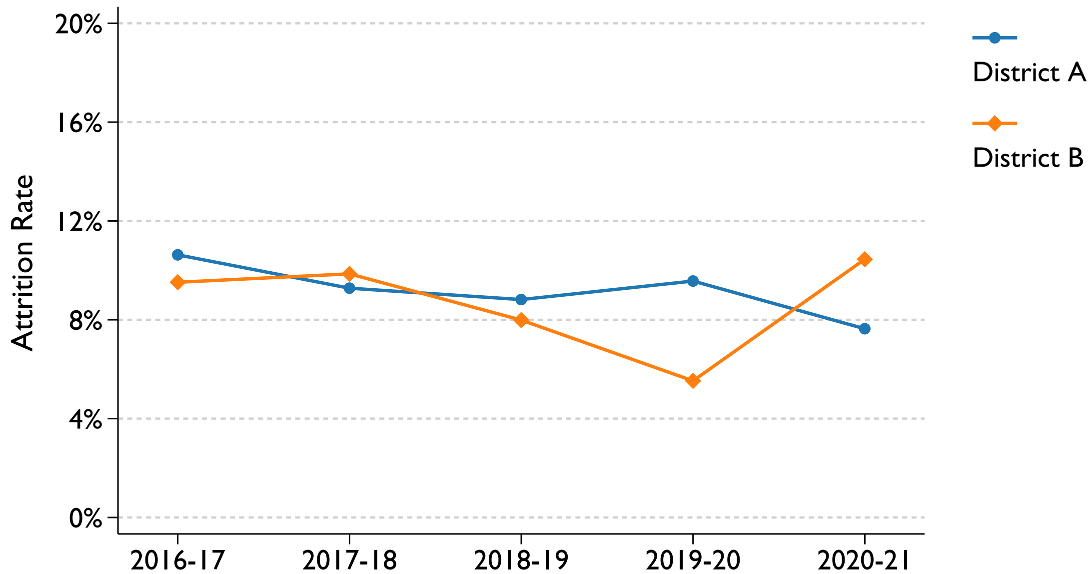


Notes. The share of new math and science teachers equals the math and science teachers who are new to teaching in the district as a percentage of active math and science teachers in each year.

In district A, the proportion of math and science teachers who are new to the district went from 6.4 percent in Fall 2019-20 to 5.1 percent in in Fall 2021-22. In district B, the proportion of new-to-district math and science teachers declined from 5.4 to 2.8 percent of the same period. Given the increase in attrition of math and science teachers in District B during the pandemic, this suggests that positions are either going unfilled or that departing math and science teachers are being temporarily replaced by long-term substitutes or non-certified personnel.

Finally, I consider the impacts of the pandemic on foreign language teachers (including traditional world language teachers and English as a Second Language teachers). As shown in Figure 2.11, attrition rates were trending downward in both District A and District B prior to the pandemic.

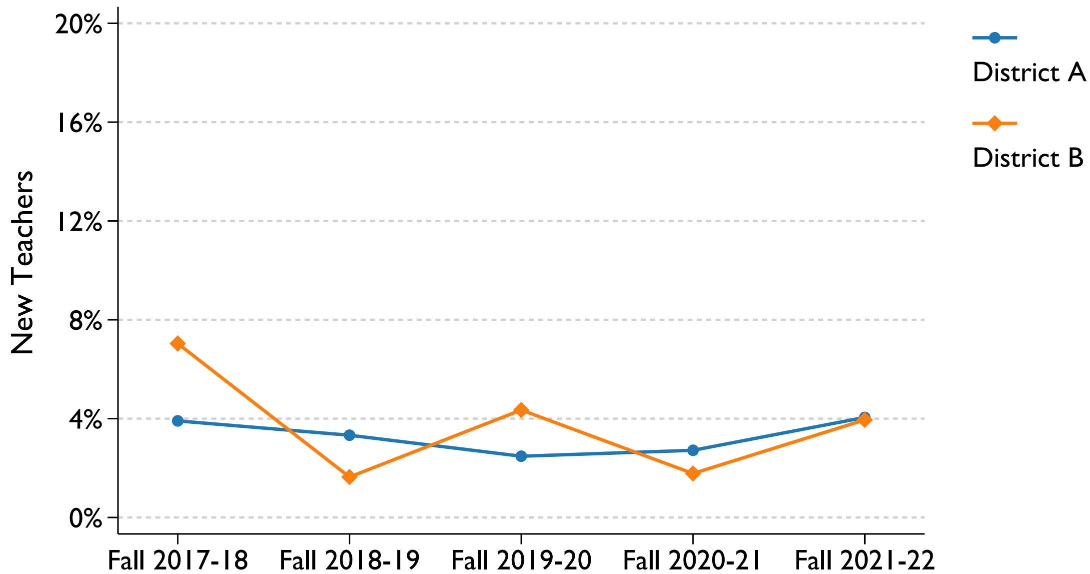
Figure 2.11. Attrition Rate for Foreign Language Teachers, SY 2016-17 to SY 2020-21



Notes. The attrition rate is the number of world language and ESOL teachers who taught in the spring of the given year who do not return to teach in the district in the following year, expressed as a percentage of active world language and ESOL teachers in the given year.

After school closures in Spring 2020, District B initially experienced about a two-and-one-half percentage point decline in attrition while the attrition rate in District A rose by less than one percentage point. Interestingly, as the general unemployment rate fell in 2021, attrition rates for foreign language teachers in District B rose (as one might expect with improved opportunities in other districts and outside of teaching), but declined in District A. As illustrated in Figure 2.12, the proportion of foreign language teachers in District A who are new to the district has risen steadily during the pandemic, despite the fact that attrition rates have declined.

Figure 2.12. Share of New Foreign Language Teachers, Fall SY 2017-18 to Fall SY 2021-22



Notes. The share of new world language and ESOL teachers equals the world language and ESOL teachers who are new to teaching in the district as a percentage of active world language and ESOL teachers in each year.

One possible explanation is that world language and/or ESL programs are expanding in the district. In District B, the proportion of new-to-district foreign language teachers varies widely from year to year; there is no clear trend over time.

2.3.2 Logistic Regression Results for Teacher Attrition

The binary logistic regression results for teacher attrition in District A are shown in table 2.1.

Table 2.1. Logistic Regression for Likelihood of Leaving Teaching in District A

Teacher Characteristic	Pre-Pandemic		SY2020		SY2021	
	(1)	(2)	(3)	(4)	(5)	(6)
Race/Eth: Black	-0.093	-0.016	-0.007	0.090	-0.111	0.090
	(0.060)	(0.075)	(0.095)	(0.101)	(0.098)	(0.101)
Race/Eth: Hispanic	-0.196*	-0.163	-0.374*	-0.313	-0.216	-0.313
	(0.117)	(0.118)	(0.195)	(0.193)	(0.184)	(0.193)
Race/Eth: Other	-0.299***	-0.274**	-0.206	-0.155	-0.424**	-0.155
	(0.103)	(0.115)	(0.164)	(0.138)	(0.173)	(0.138)
Gender: Female	-0.151**	-0.125	0.068	0.072	0.009	0.072
	(0.063)	(0.084)	(0.104)	(0.121)	(0.104)	(0.121)
Early Career (<5yrs)	0.356***	0.394***	0.769***	0.806***	0.541***	0.806***
	(0.069)	(0.056)	(0.087)	(0.090)	(0.088)	(0.090)
Late Career (>30yrs)	0.873***	0.848***	1.443***	1.418***	1.212***	1.418***
	(0.095)	(0.096)	(0.135)	(0.154)	(0.145)	(0.154)
Subject: STEM	0.067	0.080	0.074	0.077	0.016	0.077
	(0.069)	(0.066)	(0.111)	(0.095)	(0.115)	(0.095)
Subject: Foreign	-0.127	-0.038	0.115	0.147	-0.135	0.147
Language	(0.110)	(0.116)	(0.181)	(0.186)	(0.212)	(0.186)
Subject: Special	0.454***	0.461***	0.268	0.260	0.425**	0.260
Education	(0.125)	(0.164)	(0.209)	(0.273)	(0.196)	(0.273)
Elementary	-0.151	-0.051	-0.031	-0.012	0.079	-0.012
	(0.061)	(0.076)	(0.100)	(0.095)	(0.100)	(0.095)
School: % FRPM-	1.957***	.	0.386	.	1.027***	.
Eligible	(0.238)		(0.377)		(0.389)	
School: % Non-White	-2.047***	.	0.275	.	-0.922	.
	(0.342)		(0.572)		(0.578)	
School FE	No	Yes	No	Yes	No	Yes
n	8,982	8,982	7,826	7,826	7,891	7,891

Note. *p<0.1 **p<0.05 ***p<0.01. SY2020 refers to the decision of teachers who were active in the 2019-2020 school year. SY 2021 refers to the decision to stay or not of teachers who were active in the 2020-2021 school year. Results shown are coefficients from the logistic regression.

During the pre-pandemic period, teachers with less than five years of experience were 59% more likely to exit teaching in the district than mid-career (5-30 years) teachers while later career teachers with over 30 years of experience 71% more likely to exit teaching in the district than mid-career teachers. Teachers in special education were 61% more likely to exit teaching than teachers in a lower-need subject area. Further, while the specification with school fixed effects accounts for differences in student bodies, the specification without school fixed effects includes additional variables which capture information about the students at a teacher's school with both of these being significant, though only FRPM percentage is related to an increase in the likelihood of attrition. It is also interesting to acknowledge that the school fixed effect specification and the specification using proportions of FRPM and non-white students yield similar coefficients which suggests that much of the variation across schools lies in differences in the students.

Immediately following the school closures in the spring of 2020, the only groups that were significantly more likely to exit teaching in the district were those teachers with less than five years of experience and those with more than 30 years of experience with early-career teachers being 68% more likely to exit teaching and late career teachers being 81% more likely to exit. Following the 2020-21 school year, this figure dropped to 63% and 77% respectively which are both still higher than in the pre-pandemic period. However, pre-pandemic probabilities of attrition returned for special education teacher relative to teachers in lower-need subjects. Special education teachers were 60% more likely to exit teaching than teachers in lower-need subject areas, though this figure is only significant for the specification without school fixed effects which suggests that there may have been different compositions of special education teachers in different schools during this time. Further, while student characteristics did not significantly impact the likelihood of attrition following school closures, the coefficient on FRPM percentage is significant following the 2020-21 school year.

I show the binary logistic regression results for teacher attrition in District B in Table 2.2.

Table 2.2. Logistic Regression for Likelihood of Leaving Teaching in District B

Teacher Characteristic	Pre-Pandemic		SY2020		SY2021	
	(1)	(2)	(3)	(4)	(5)	(6)
Race/Eth: Black	-0.260***	-0.056	-0.392***	-0.330***	0.189*	0.120
	(0.066)	(0.060)	(0.122)	(0.125)	(0.108)	(0.110)
Race/Eth: Hispanic	-0.031	0.087	-0.613	-0.590	0.351	0.315
	(0.182)	(0.181)	(0.473)	(0.474)	(0.297)	(0.260)
Race/Eth: Other	-0.068	0.017	-0.346	-0.322	-0.193	-0.218
	(0.159)	(0.152)	(0.316)	(0.311)	(0.286)	(0.314)
Gender: Female	-0.041	-0.068	0.006	-0.006	-0.056	-0.052
	(0.065)	(0.070)	(0.122)	(0.124)	(0.099)	(0.096)
Early Career (<5yrs)	0.279***	0.286***	0.329***	0.335***	0.460***	0.455***
	(0.055)	(0.061)	(0.116)	(0.119)	(0.099)	(0.098)
Late Career (>30yrs)	0.346***	0.359***	1.126***	1.130***	0.498***	0.501***
	(0.108)	(0.112)	(0.163)	(0.151)	(0.161)	(0.162)
Subject: STEM	0.301***	0.304***	0.326**	0.331**	-0.003	-0.002
	(0.076)	(0.082)	(0.138)	(0.155)	(0.115)	(0.103)
Subject: Foreign Language	-0.128	-0.152	-0.469*	-0.479**	-0.253	-0.259*
	(0.114)	(0.110)	(0.239)	(0.241)	(0.173)	(0.144)
Subject: Special Education	-0.685***	-0.710***	-1.161***	-1.159***	-2.748***	-2.749***
	(0.110)	(0.121)	(0.276)	(0.230)	(0.416)	(0.432)
Elementary	0.215***	0.184**	0.259**	0.252**	-0.071	-0.074
	(0.065)	(0.083)	(0.121)	(0.128)	(0.100)	(0.106)
School: % FRPM-Eligible	-1.062***	.	-0.748	.	-0.270	.
	(0.220)		(0.501)		(0.520)	
School: % Non-White	2.261***	.	1.100*	.	-1.863	.
	(0.315)		(0.643)		(0.608)	
School FE	No	Yes	No	Yes	No	Yes
n	7,571	7,571	6,047	6,047	5,864	5,864

Note. *p<0.1 **p<0.05 ***p<0.01. SY2020 refers to the decision of teachers who were active in the 2019-2020 school year. SY 2021 refers to the decision to stay or not of teachers who were active in the 2020-2021 school year. Results shown are coefficients from the logistic regression.

During the pre-pandemic period, District B had similar trends to District A with early-career teachers and late-career teachers having the highest probabilities of attrition. Teachers with less than five years of experience were 57% more likely to exit teaching in the district than mid-career teachers while teachers with over 30 years of experience were 59% more likely to exit teaching in the district. Further, teachers in STEM subjects were 57% more likely than teachers in lower-need subjects to exit teaching in the district. Finally, teachers in elementary grades were 55% more likely than middle and high school teachers to exit teaching. Interestingly, special education teachers were significantly less likely to exit teaching in the district with the probability of exit for special education teachers being 34% lower than teachers in lower-need subject areas. In addition, as the specification without school fixed effects includes variables for student characteristics in a teacher's school, I observe a that teachers in a school which a higher proportion of non-white teachers are significantly more likely to exit teaching while teachers in a school with a higher proportion of FRPM-eligible students are significantly less likely to exit.

After the school closures in spring of 2020, the probability of a teacher exiting relative to mid-career teachers increases for early- and late-career teachers (58% and 76% respectively without school fixed effects). The likelihood of a STEM teacher exiting also increases relative to teachers in lower-need subjects while the likelihood of a special education teacher exiting decreases relative to teachers in lower need subjects. Following the 2020-21 school year, early career teachers continue to experience an increase in their probability of attrition while late-career teachers see a return to the probability of attrition as in the pre-pandemic period; the probability of attrition for teachers in STEM subjects is no longer significant compared to teachers in lower-need subject areas; and special education teachers continue to have a significantly lower probability of exiting compared to teachers in lower-need subject areas.

2.3.3 Multinomial Logistic Regression Results for Teacher Mobility

While this study has mainly considered the binary decisions to stay in the district or to leave, teachers face many other choices including decisions to change schools within a district, move to teach in another district, or to leave teaching all together. Teacher mobility is important to school districts as mobility within a district may exacerbate inequalities in the distribution if teacher quality (i.e. if a teacher with more experience moves to a school that is perceived to be better). Further, movement to another district is equivalent to attrition from the original district's perspective so districts may be concerned with losing good teachers to other school districts. I employ a multinomial logistic model to understand the non-binary decisions that teachers face. As district A did not provide information on why a teacher chose to leave the district, I am only able to consider the decisions to switch schools within the district or to leave teaching in the district. Further, as information on a teacher's school at the start of the 2021-22 school year was unavailable, I only consider teacher mobility decisions in the pre-pandemic period and immediately following the school closures in spring of 2020 where a decision to switch schools is defined as a teacher working in a different school in fall of 2020 than in spring of 2020 and a decision to leave is defined as a teacher who was an active teacher in the district in spring of 2020 but not in fall of 2020. I run each regression using school fixed effects. The results for the multinomial logistic regression for District A are shown in Table 2.3.

Table 2.3. Multinomial Logit Regression for Teacher Mobility Decisions District A

Teacher Characteristic	Pre-Pandemic		SY 2020	
	Switch (1)	**Leave (2)**	**Switch (3)**	**Leave (4)**
Race/Eth: Black	0.000	-0.025	0.012	0.086
	(0.080)	(0.079)	(0.121)	(0.105)
Race/Eth: Hispanic	0.069	-0.119	0.180	-0.286
	(0.144)	(0.133)	(0.175)	(0.196)
Race/Eth: Other	-0.157	-0.247*	-0.097	-0.194
	(0.114)	(0.132)	(0.168)	(0.146)
Gender: Female	-0.158*	-0.106	0.053	0.089
	(0.084)	(0.079)	(0.085)	(0.119)
Early Career (<5yrs)	-0.059	0.339***	-0.143	0.782***
	(0.072)	(0.057)	(0.102)	(0.090)
Late Career (>30yrs)	0.161	0.859***	-0.362**	1.368***
	(0.132)	(0.103)	(0.183)	(0.156)
Subject: STEM	-0.013	0.118	0.029	0.076
	(0.092)	(0.086)	(0.077)	(0.096)
Subject: Foreign Language	-0.402***	-0.143	-0.565***	0.060
	(0.141)	(0.124)	(0.160)	(0.183)
Subject: Special Education	0.030	0.448***	-0.182	0.228
	(0.109)	(0.169)	(0.235)	(0.278)
Elementary	-0.412***	-0.136	-0.679***	-0.116
	(0.109)	(0.084)	(0.138)	(0.100)
School FE	Yes	Yes	Yes	Yes
n	8,996	8,996	7,828	7,828

Notes. *p<0.1 **p<0.05 ***p<0.01. “Switch” denotes a teacher who moves to another school within the district. “Leave” denotes a teacher who does not return to teach in the school district. SY2020 refers to the mobility decision of teachers who were active in the 2019-2020 school year. Results shown are coefficients from the logistic regression.

Pre-pandemic, the probabilities for various subgroups that a teacher leaves are similar to those shown in the logistic regression. Additionally, teachers in foreign languages and in elementary grades are significantly less likely to switch schools. When considering the period immediately following school closures, the results for teachers who leave the district are similar to those found in the logistic regression model. As in the pre-pandemic period, teachers in foreign language subjects and in elementary grades had a significantly lower probability of switching schools within the district than teachers in middle and high school grades. Unlike during the pre-pandemic period, late-career teachers were much less likely to switch schools within the district.

I estimate a similar model for teacher mobility decisions in District B. As this district provided detailed information on the reasons that a teacher left the district, I consider four different mobility decisions, including the decision to stay in the same school, switch schools within the district, move to another district in Georgia, or leave teaching in Georgia. The decision to move is defined as a teacher being listed as having moved to another district in the fall who was active in the district in the previous spring; the decision to leave is defined as a teacher who is active in the given spring semester but is not listed as active or as having moved districts in the following fall semester. As the school a teacher is employed in not available for the 2021-22 school year, the three decisions for spring 2021 are to stay in the district (Stay), to move to another district in Georgia (Move), or to leave teaching in Georgia (Leave). The results for District B are shown in Table 2.4.

Table 2.4. Multinomial Logit Regression for Teacher Mobility Decisions District B

Teacher Characteristic	Pre-Pandemic			SY 2020			SY 2021	
	Switch (1)	**Move (2)**	**Leave (3)**	**Switch (4)**	**Move (5)**	**Leave (6)**	**Move (7)**	**Leave (8)**
Race/Eth: Black	0.452***	0.242	-0.080	0.415**	0.026	-0.357***	-0.041	0.145
	(0.132)	(0.157)	(0.060)	(0.201)	(0.351)	(0.134)	(0.243)	(0.116)
Race/Eth:	0.388*	0.847**	-0.026	0.501	.	-0.436	0.531	0.266
Hispanic	(0.225)	(0.338)	(0.206)	(0.498)		(0.476)	(0.641)	(0.282)
Race/Eth: Other	0.520**	0.058	0.111	0.059	.	-0.210	0.415	-0.375
	(0.204)	(0.399)	(0.166)	(0.504)		(0.324)	(0.493)	(0.359)
Gender: Female	0.027	0.254*	-0.090	0.121	0.145	-0.018	-0.520**	0.027
	(0.093)	(0.141)	(0.079)	(0.211)	(0.379)	(0.128)	(0.238)	(0.106)
Early Career	-0.043	0.098	0.325***	0.313*	0.017	0.391***	0.042	0.515***
(<5yrs)	(0.079)	(0.137)	(0.071)	(0.179)	(0.339)	(0.123)	(0.262)	(0.099)
Late Career	-0.171	.	0.538***	-0.531	-0.937	1.248***	.	0.674***
(>30yrs)	(0.149)		(0.116)	(0.392)	(0.987)	(0.153)		(0.162)
Subject: STEM	-0.062	0.152	0.343***	-0.028	0.480	0.310*	-0.089	0.012
	(0.121)	(0.185)	(0.091)	(0.244)	(0.382)	(0.167)	(0.311)	(0.108)
Subject: Foreign	-0.006	-0.321	-0.123	-0.038	0.343	-0.607**	0.048	-0.314*
Language	(0.158)	(0.294)	(0.124)	(0.305)	(0.529)	(0.277)	(0.390)	(0.171)
Subject: Special	-0.550***	-0.820***	-0.781***	-0.444*	-0.956	-1.205***	-2.440**	-2.800***
Education	(0.154)	(0.287)	(0.137)	(0.267)	(0.689)	(0.256)	(0.970)	(0.416)
Elementary	-0.430***	0.305*	0.120	-0.480*	0.202	0.238*	-0.049	-0.077
	(0.158)	(0.155)	(0.092)	(0.264)	(0.388)	(0.134)	(0.229)	(0.107)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	7,571	7,571	7,571	6,049	6,049	6,049	5,864	5,864

Notes. *p<0.1 **p<0.05 ***p<0.01. “Switch” denotes a teacher who moves to another school within the district. “Moves” denotes a teacher who moves to teach in another school district in Georgia. “Leave” denotes a teacher who does not return to teach at any school in Georgia. SY2020 refers to the mobility decision of teachers who were active in the 2019-2020 school year. SY 2021 refers to the mobility decision of teachers who were active in the 2020-2021 school year. Results shown are coefficients from the logistic regression. Empty cells are categories with zero teachers.

During the pre-pandemic period, early career teachers, late-career teachers and teachers in STEM subjects had the highest probability of leaving the profession with special education teachers having a much lower probability of leaving. It is important to note that, while these results are similar to the logistic regression results, they are not as close as in District A due to the fact that this model considers leaving teaching in Georgia while the logistic regression model considers leaving teaching in the district (both models for District A consider only leaving teaching in the district). Hispanic teachers and female teachers had higher probabilities of moving to another district than White teachers and male teachers respectively while special education teachers had a much lower probability of moving districts than teachers in lower-need subjects and elementary teachers had a significantly higher probability of moving to another district than middle and high school teachers. There were no teachers with more than 30 years of experience who chose to move to another district during the pre-pandemic period (see Appendix Table A2). White teachers had a much lower likelihood of switching schools within the district than did teachers of other races and ethnicities. Special education teachers had a significantly lower probability of switching than did teachers in lower-need subject areas and elementary teachers had a significantly lower probability of switching than did middle and high school teachers.

Immediately following the school closures in spring of 2020, teachers with the highest likelihood of leaving teaching in Georgia included both early- and late-career teachers with Black teachers, foreign language teachers, and special education teachers having the lowest likelihood of leaving. There were no significant differences between groups in the likelihood of moving districts, though it is important to acknowledge that the number of teachers who moved districts during the period was very low and that no teachers who did not identify as Black or

White made the decision to move districts (see Appendix Table A2). There was also little variation in the likelihood of a teacher switching schools in the district. Following the 2020-21 school year, early- and late-career teachers were significantly more likely than mid-career teachers to leave teaching in Georgia and special education teachers were significantly less likely to leave. Further, female and special education teachers were significantly less likely to move to another district in Georgia.

2.4. Discussion

2.4.1 Limitations and Concerns

The data unfortunately do not allow for causal analysis as there may be unobserved factors that impact teacher mobility decisions. However, the rich descriptive information obtained from this study is some of the first quantitative evidence on the impacts of the pandemic on teacher labor markets in metro-Atlanta. This study is both beneficial to the participating districts and as well as to education researchers in general. Specifically, our partner districts are able to use this information to better understand how their teachers were impacted by the COVID-19 pandemic. In addition, the results from this analysis can be used to inform policy recommendations that will help the districts to retain teachers as we emerge from the COVID era. This study also considers a short time period after the start of the pandemic. As circumstances continue to change, this study provides a starting point for future work on the long-term impacts of the pandemic in the participating districts.

2.4.2 Conclusion

In this chapter, I examine attrition and hiring trends of teachers in two metro-Atlanta school districts before and after the onset of the COVID-19 pandemic using descriptive methods and logistic regressions. In both districts, I find that attrition decreased immediately following the school closures in the spring of 2020 as the pandemic also came with greater labor market uncertainty. However, attrition rates have since increased in both districts with attrition in District A remaining lower than what pre-pandemic trends predicted and attrition in District B being slightly higher.

One new concern during the pandemic was that the transition to virtual instruction may be more difficult for older teachers and therefore lead older teachers and those with more experience to retire early. Further, the additional difficulties with teaching during the pandemic may have led to greater turnover of early-career teachers. I find that attrition rates for teachers with 30 or more years of experience had been increasing since at least SY 2016-17 which is similar to what is observed when only considering retirements in District B. As for teachers with less than 5 years of experience, I find that attrition had been trending down in District A and has since leveled off further, and I find that attrition had been on an upward trend in District B, but current attrition levels are lower than pre-pandemic trends predicted. Finally, I consider attrition of mid-career teachers but find little variation pre- and post-pandemic.

I also consider trends in the hiring of new teachers. In both districts, the proportion of teachers who are new decreased immediately following the school closures in spring of 2020 but hiring rates have since increased. The decrease in hiring may be related to the previous finding of a drop in attrition rates as there were fewer vacancies to be filled by the districts. While the proportion of new teachers in District A has returned to pre-pandemic levels, the proportion of new teachers in District B remains lower than pre-pandemic trends predicted. However, District B has experienced a decrease in student enrollment following the onset of the pandemic. Therefore, I observe that teacher-student ratios in each district remain constant over time suggesting that average class sizes have remained constant despite changes in teacher labor markets.

Finally, I consider changes in teacher attrition and hiring in hard-to-staff subject areas including special education, math and science, and foreign languages. I find that, despite fluctuations in overall attrition rates, the pandemic does not appear to have led to a worsening of teacher attrition in these subject areas. However, the proportion of math and science teachers that are new to the district has declined substantially during the pandemic in both districts which suggests that positions either have gone unfilled or that positions may have been filled by non-certified personnel or long-term substitutes, particularly in District B. I also observe a steady increase in new foreign language teachers in District A, possibly due to expanded world language and/or ESL programs in the district.

In addition to providing summary statistics, I also estimate logistic regression models that provide insight into which teacher characteristics have been most related to teacher attrition and mobility before and during the pandemic era. As suggested in the literature, both districts saw that teachers with less than five years of experience and teachers in STEM subjects were the most likely to leave teaching in their given district before the start of the pandemic with the two districts having mixed results for special education teachers. After the start of the pandemic, early career teachers in District A had a higher likelihood of leaving and STEM teachers in District B had a higher likelihood of leaving. Attrition trends in both districts returned to levels that were comparable to the pre-pandemic period after a year of virtual and hybrid instruction. The multinomial logistic regressions further explored teacher decisions to switch schools within a school district or to switch school districts. While many subgroups faced higher likelihoods of switching schools or moving districts before the start of the pandemic, many of these differences went away after the start of the pandemic.

Overall, while there have been changes in attrition and teacher hiring over time, most post-pandemic observations appear to be related to pre-pandemic trends. Further, I do not find evidence of any new teacher labor market concerns, particularly with older teachers. Our only observation regarding potential impacts of the pandemic is the decrease in new hires in District B but this appears to be largely explained by changes in student enrollment. Our findings suggest that districts should consider long-term programs that target existing working conditions rather than short-term solutions that are intended to curb pandemic-related effects. Specifically, districts may consider programs that target teacher satisfaction such as mentoring programs, continuing education programs, and increased administrative support and collaboration (See et. al., 2020; Van der Vyver et. al., 2020; Whitfield et. al., 2021). In addition, districts may consider pay-related programs such as salary increases or student loan forgiveness rather than short-term bonuses that may be less effective for retaining teachers (Clotfelter et. al., 2008; Feng, 2009; Feng & Sass, 2017; See et. al., 2020; Schwartz, 2021).

As every school district faces different circumstances, including the two in this study, it is important to recognize that these results may not generalize to other districts even in the state of Georgia. However, the results of this study are similar to those found in other areas of the country. For instance, researchers have found that recent attrition rates in Washington State are comparable to attrition rates pre-pandemic (Goldhaber & Theobald, 2022). Additionally, studies of teachers in Arkansas and Massachusetts found that retention was relatively stable immediately following school closures and that attrition rates increased at the end of SY2020-21 (Camp et. al., 2022; Bacher-Hicks et. al., 2022). Further research should be done to understand whether these observed trends continue into the future and whether they can be applied to more districts in the metro-Atlanta area and in the state of Georgia.

Chapter 3: The Impacts of a Classroom Game on Student Understanding of Environmental Policy (Joint with Caroline Lamprecht)

3.1 Introduction

Recent surveys have shown that the majority of students, parents, and teachers would like climate change to be taught in schools; however, most schools do not teach about climate change beyond a simple mention of the topic (Kamenetz, 2019; Kwauk & Winthrop, 2021). In fact, when asked why climate change is not a part of the curriculum, teachers report reasons such as it not being related to their subject, lack of resources, lack of support from their school district, and little interest from students. Research has shown that teaching students about carbon emissions and climate change is related to a significant reduction in carbon emissions by students, and students report a stronger personal relationship to climate change solutions (Cordero et. al., 2020). These attitudes are measured using a series of pre and post-game surveys.

There is a significant body of literature which looks at the use of classroom games to teach economic concepts, including market structures and game theory, and shows that games can be used to increase student engagement and performance in class (Nungsari & Flanders, 2020; Lin, 2018; Moinas & Pouget, 2016; Durham et. al., 2007). Given that there is evidence that teaching about climate change solutions can have a positive impact on the environment attitudes of students and given that there is a demand for climate change and environmental education, this study aims to examine the impact of using a classroom game to teach carbon trading schemes on student attitudes towards climate change and environmental policy. Specifically, this study considers undergraduate students in introductory-level economics courses and suggests that exposing students to an environmental policy solution through a classroom game may increase student engagement with economics and environmental policy as well as impact their attitudes and personal relationship to climate change.

This paper considers a field experiment[8] with a difference-in-difference approach where undergraduate economics students take part in an emissions trading game based on a 2019 paper by Carattini and colleagues. Course sections are assigned to participate in a classroom session which includes a brief discussion on carbon trading policies and playing the emissions trading game. Additionally, all students who take part in the study complete two surveys, one before and one after the game was played. Within the survey, we also evaluate the change in knowledge of carbon trading policies between the treatment and control group using exam-type questions on carbon trading. The first question that we answer is whether this classroom game is an effective method for teaching students about environmental policy, and specifically market-based policies. The second question is whether teaching environmental policy can shape student attitudes towards the use of environmental policy. This study not only has implications for environmental policy, but also for environmental economics pedagogy as it both provides a method to examine the importance of environmental education and provides a specific tool to be used in teaching environmental course material.

3.1.1 Classroom Games

This study builds on the literature on the effectiveness of classroom games in teaching economics. Active learning methods have been shown to be much more effective in teaching STEM-related subjects and economics as compared to traditional lecture, with games and experiments being among the most effective active learning methods (Emerson & Taylor, 2004; Dickie, 2006; Durham et al., 2007; Freeman et al., 2014). In addition, the use of classroom

[8] Registered with the AEA RCT Registry. RCT ID: AEARCTR-0010166

games can positively impact student engagement and attendance in a course, and they have been found to be highly effective in teaching complicated topics to students including topics such as market structures and Bayes Rule (Holt & Anderson, 1996; Lin, 2018; Nungsari & Flanders, 2020).

The literature on classroom games for teaching environmental economics has also been growing in recent years with numerous different active learning techniques and environmental economics games relating to a variety of topics including common-pool resource dilemmas and externality-correcting taxes being studied (Castro-Santa, 2023; Duke & Sassoon, 2017; Farolfi & Erdlenbruch, 2020; Holt, 1999). Additionally, this study is not the first to consider a pollution-related or emissions trading game but is among the first to study the impacts of a game relating to emissions trading policy (Ando, 2006; Corrigan, 2011; Caviglia-Harris & Melstrom, 2015). Thus, the literature suggests that using a carbon trading game as this study does should positively impact student understanding of an emissions trading policy. In turn, we could expect that this game may also address information asymmetries and student attitudes towards environmental policy.

3.1.2 Emissions Trading Policies and Information Asymmetries

Because the game used in this study considers emissions trading schemes, it is important to consider the literature on emissions trading policies as the intention of teaching about such a policy is to shape student attitudes towards environmental policy in general. Emissions trading schemes have become a well-known policy tactic to manage carbon emissions with such policies being used in multiple countries, states, and individual firms (Newell & Rogers, 2003; Victor & House, 2006; Voß, 2007; Ellerman et al., 2016). While popular, these schemes have more importantly been shown to be highly effective at reducing costs related to pollution including health-related costs (Burtraw, 1998; Chestnut & Mills, 2005; Barreca et al., 2017). As emissions trading schemes have become more popular and effective, it is also important to note the economics behind these schemes which is important when teaching about these policy mechanisms to students. Emissions trading schemes work by allocating emissions permits to parties which can then be traded among other parties in the market based on individual comparative advantages. Therefore, as emissions trading schemes are market-based policies, they theoretically should yield greater economic welfare than command and control policies which are often thought of as the alternative policy (Muller & Mendelsohn, 2009). In theory, the emissions cap set by the available permits should be set at the socially optimal level, though it will improve welfare so long as it is binding (Carattini et al., 2020).

This study also relates to a broader literature on information asymmetries, especially as we are considering impacts of playing a game on attitudes towards environmental policy. In particular, preferences in favor of the environment may not perfectly translate to support of particular policies. However, many researchers have found that exposure to an environmental policy through a trial period may increase public support for a particular policy (Cherry et. al., 2014; Carattini et. al., 2018). Further, researchers have found that exposure to information on certain policies may increase support (Carattini et al., 2017; Dal Bó et. al., 2018; Douenne & Fabre, 2022). Therefore, teaching about cap-and-trade policies may lead to a reduction in information asymmetries through increasing knowledge of the policies and therefore changing attitudes towards carbon trading.

3.2 Empirical Approach

3.2.1 Experimental Method

This study employs a field experiment with a difference-in-difference approach which includes three components: two surveys and an in-class game. The study uses participants from undergraduate classes at a large public university. The original version of the game entitled “For Want of a Chair” works like a game of musical chairs where a “chair” represents an allowance for a “firm,” in this case played by a student, to emit pollutants, and is based on a 2019 paper by Carattini and colleagues. After students are allocated a certain allowance of carbon production, they will have the opportunity to trade with other students, including those who are not allocated any allowances. This interaction demonstrates how a cap-and-trade carbon trading scheme works.

In the current study, chairs are allocated through a random number generator on the virtual platform on the facilitator’s computer. The game was facilitated in ClassEx, a virtual economics game platform, which presented students with their private value of having or not having a chair and tracked the trades that students choose to make. Each time the game was played, an outside facilitator (someone other than the course instructor) was present to explain the rules of the game and to give a brief lesson on carbon trading policies. On the day of the game, the facilitator introduced themselves, introduced the game and the procedures, then began the “lesson” on cap-and-trade policies using the game. The facilitator used about 30 minutes at the start of a section’s regular class time, after which the course instructor resumed regular instruction.

To ensure a control group, half of the participating classes were assigned to play the game in class while the other half only completed the surveys. Assignment was based on the willingness of instructors as the game used a significant portion of their class time and thus we were unable to employ true random assignment. Students in the control group received no instruction on cap-and-trade policies in their economics course. Further, the experiment was delivered during the middle of the semester after students in microeconomics courses had been introduced to the concept of externalities so that students would not receive additional instruction on environmental policy during the course of the experiment. All students were offered extra credit points in collaboration with the participating instructors for attending class and participating in the surveys. While the specific terms of the extra credit given were up to individual instructors, the extra credit ranged from three to five points on an exam.

All students were given two surveys, one before the day the game was played and one after the game was played, with both being approximately one week away from the date of the in-class game (or approximately two weeks apart for sections in the control group). The surveys included a quiz on cap-and-trade policies to evaluate student understanding of the policy. The full quiz can be found in Appendix 1. The survey also asked students questions on demographic and other individual characteristics as well as questions to elicit attitudes towards the environment. These questions can be found in Appendix 2. The questions on student characteristics included student race and ethnicity, gender, area of study, political leanings, family income, and voting activity in the 2022 election. In addition, students were asked about their interest in economics, their belief that classroom activities are beneficial for learning, their experience with economics games, and their attitude towards playing the game (treatment group only). It is important to note that all of these questions are based on self-response as FERPA guidelines did not allow for actual student data to be used in the current study. The questions on environmental attitudes have been adapted from various survey inventories to ensure that the questions used are valid and reliable.

3.2.2 Data

The participants for this study included students from principles-level economics courses at a large public university. Students were offered extra credit towards a future exam for participation in the research study, with the specific extra credit amount being at the discretion of the participating instructors. The participants included students from two Principles of Macroeconomics sections and five Principles of Microeconomics sections with most of the participants being freshmen or sophomores in business-related majors. All students in the courses were invited to take a pre-game survey with the understanding that extra credit would be given for completing all of the components of the experiment depending on their treatment assignment. For the treatment groups, this included completing both surveys and attending class on the day of the game. For the non-treatment groups, this just included completing both surveys.

Appendix Tables C1a-C1e show the characteristics of the students who participated in the study as well as demographic characteristics of the business school at the university at which the participants attend. While we did not have access to administrative data on student characteristics, our survey asks students to report demographic characteristics including gender, race, age, and major, as well as characteristics such as political affiliation and likelihood of voting in the 2022 midterm election as the experiment took place before election day. Based on the responses of students who took the first survey, the treatment and control groups appear to be homogenous, especially when considering socioeconomic status and political affiliations, so we argue that the two groups are balanced on observables. Further, the final sample of students who completed both surveys gave treatment and control groups that were fairly similar. Finally, we consider scores on the cap-and-trade knowledge questions and the environmental attitudes questions. We observe that cap-and-trade knowledge scores for the treatment and control groups are fairly balanced with the control group receiving an average score of 4.5 out of 10 and the treatment group receiving an average score of 4.1 out of 10. We also find that the environmental attitude scores of the two groups were similar on the first survey with the control group receiving an average score of 65.2 out of 100 and the treatment group receiving an average score of 64.7 out of 100.

It is important to note that not all students who took the preliminary survey attended class on the day of the game or completed the follow-up survey with 34% of students in the treatment group who completed the first survey also completing the second, and 63% of students in the control group who completed the first also completing the second. In total, 181 students in the control sections took the initial survey while 199 students in the treatment sections took the initial survey. These numbers dropped to 57 students in the control sections and 104 students in the treatment sections who took the second survey. In addition, there was not perfect compliance with the treatment as some students in the treatment sections left class early, arrived late, or did not attend class despite having completed one or both of the surveys. As we do not have information on compliance, we perform an intent-to-treat analysis for the students who completed both surveys.

3.3 Results

3.3.1 Student Knowledge of Policy

The main goal of this study is to understand whether playing a cap-and-trade game is an effective tool for teaching students about environmental policy. To measure this, we compare student scores (out of 10) on a mock quiz which covers cap-and-trade policy concepts that were covered during the game that students played in class. We not only evaluate the difference between the two groups on their scores on the second quiz, but we also employ a "difference-in-difference" approach to account for any differences in student knowledge beforehand. Thus the three regressions consider the outcomes of student scores on the first survey, student scores on the second survey, and the change in scores between the two surveys. Average scores for students who took both surveys are shown in Appendix Table C2. We do not find any significant difference between the two groups on the post-game quiz. However, we observe that students in the treatment group who took both surveys performed much worse on the initial quiz. This implies that, despite little difference on the second quiz, the students in the treatment group may have shown more improvement. Thus, we evaluate the impact of being assigned to play the game on differences between the two quizzes, shown in Table 3.1.

Table 3.1. Regression Results for Student Cap-and-Trade Quiz Scores

	Pre-game	Post-game	Difference	Section Fixed Effects
Assigned to Play Game	-.727** (.292)	-.052 (.353)	.675* (.352)	No
Assigned to Play Game	-.727** (.226)	-.052 (.261)	.628* (.369)	Yes
N	160	160	160	

Note. Standard errors are shown in parentheses. In the section fixed effects case, standard errors are clustered at the section level. The "Difference" regression uses the outcome variable of the change in scores between the two surveys.

We find that the students in the treatment group improved their scores 63% more than did students in the control group. These results are similar with section fixed effects which are employed to account for variation across sections. However, the coefficient on the difference in student scores is no longer significant when accounting for various descriptive characteristics (see Appendix Table C3). These results suggest that playing the game may have had small impacts on student learning. However, the observed impacts may have been due to differences in the students who selected to complete both surveys, especially given differences between the two groups in initial scores.

3.3.2 Student Attitudes Towards Policy

In addition to understanding whether the game impacted student knowledge, we also wanted to know whether playing a game focused on environmental class in a course that is not focused on environmental policy may shape student attitudes towards policy. To measure this, we asked students various questions regarding their attitudes towards environmental policy and gave students a score out of 100 (with 100 being very strong positive attitudes towards the environment) with average scores for students who took both surveys shown in Appendix Table C4 and regression results (including demographic controls) shown in Appendix Table C5. In general, we did not find that playing the game impacted student attitudes towards policy, with both the treatment and control groups scoring an average 66 points on the environmental attitudes survey (following an average score of 65 points on the pre-survey for both groups). We also find that the highest environmental attitude scores belong to students who identify as female, black, or who most closely align with the Democratic or Green parties on environmental issues, with these predictors holding for both the pre-game and post-game surveys. These results suggest that a short-term game may not be effective for shaping student attitudes towards a specific topic; however, further consideration should be given towards a longer-term intervention that may be more successful at changing student attitudes towards policy.

3.3.3 Student Engagement

Many studies of the impacts of classroom games have noted increased student engagement as a result of playing games in class. While we were unable to directly measure this, we did ask students questions to begin to gauge the impacts of this game on engagement. First, of the students who played the game, 53% reported that they enjoyed playing the game with 37% reporting that they felt indifferent about the game and 10% reporting that they did not enjoy playing the game. We then asked all of the respondents about their attitudes towards economics and classroom activities. The results for student engagement are shown in Appendix Table C6. Both the treatment and control groups reported similar attitudes towards taking economics classes (see table A2c). Regarding the question of how students think that class activities impact their learning of real-life applications, the treatment group initially had a higher proportion of students respond that they do not find class activities to be very effective; however, this reversed following the game with student responses changing much more for the treatment group.

On the question of whether students feel more engaged when their professor is not just lecturing, we find a similar trend of students in the treatment group initially reporting lower engagement but reporting a much greater change following the game. These results suggest that the game impacted how students feel about playing classroom games and that games may increase engagement among students. Further, instructors of the treatment section reported that their students seemed to be more engaged following the class period where the game was played and that students continued to ask for games and interactive activities in class. However, it is important to note that the students in the treatment sections reported lower attitudes towards engagement methods. Thus, while a greater increase in scores is promising, there may be underlying differences in the treatment and control groups that we are unable to distinguish.

3.4 Discussion

This study examines the impact of a classroom game about cap-and-trade policies on student attitudes towards environmental policies. The experiment consists of three parts including a preliminary survey, a post-game survey, and an in-class game in which undergraduate economics classes were assigned to play or not. We find that the game had minimal impacts on student attitudes towards the environment, although this may be due to the fact that the game was a one-time event and did not last long. Additionally, we observe that the majority of students report a more liberal political leaning on environmental issues. Combined with relatively high scores on the environmental attitudes survey, we conjecture that students were unlikely to change attitudes in favor of the environment much. However, we do find evidence to suggest that the game was moderately effective for increasing student knowledge of cap-and-trade policies. While the groups' scores on the second survey were similar, the difference in scores was much greater and we observed a significant decline in scores for the control group. This suggests that, while students in the control group may have been better at guessing initially, students in the treatment group retained some knowledge from the class activity. We hypothesize that the game may be more effective in an environment where the topic is explored more in lectures or where student knowledge is tested with higher stakes. Finally, we have suggestive evidence that the game helped to increase student engagement and their attitudes towards active learning methods. We hypothesize that playing games such as this one more regularly could impact student performance by increasing their interest in economics and increasing attendance.

3.4.1 Limitations and Next Steps

One problem with the present study was the small sample size. This was in part because the study lost participants at each stage of the procedure, with many more students participating in the preliminary survey than the follow-up survey. Related to the small sample size and study attrition is the issue that the final samples were not balanced. While the initial treatment and control groups were balanced on observables, we notice differences in the students who took both surveys which may have ultimately impacted the regression results. We intend to run future trials to increase the sample size, particularly for the control group as more students in the treatment group completed both surveys. Another concern with the study is that it was not a true randomized control trial as students and class sections were not randomly assigned to the treatment or control group. While random assignment would have been ideal, we felt it was important to consider the time and interest of the faculty members who participated in the experiment. Additionally, there is a concern that running the experiment outside of a course may have disincentivized students from properly engaging with the experiment. While directly encouraging students to take notes may result in the survey measuring notetaking skills rather than learning, it is possible in future trials to incentivize correct responses on the survey to increase engagement and learning during the activity.

Finally, one may be concerned that we are only comparing the game to not playing the game and not to a traditional lecture on the same topic. Given the additional benefits of classroom games including increased engagement and attendance, we did not feel that comparing learning outcomes from this game and lecture was appropriate as we assume that playing a game will come with the additional benefits. Therefore, as long as the game was effective for improving learning outcomes, this game should be superior to traditional lecture. Future trials of this experiment will include additional questions to understand student engagement. Further, future study may consider the effectiveness of the game compared to traditional lecture. We will also work with instructors to increase participation in both surveys by encouraging students to take the surveys during class time. We also note the question of persistence as there may have been impacts on student learning or attitudes that went away between the time of the game and the survey. While we gave the follow-up survey within a week of when students in the treatment group played the game, in future trials we will consider giving the survey during class on the day the game is played to remove any impacts from a lack of persistence.

3.4.2 Conclusion

In this chapter, we explore the impacts of a classroom game that is intended to teach students about cap-and-trade policies. We employed a field experiment with a difference-in-difference approach to compare student knowledge of and attitudes towards policy between students who played the game in class and students who did not. We find that the game had modest impacts on student learning and minimal impacts on student attitudes. We also find suggestive evidence that the game may have been effective for increasing student engagement. This study has implications for pedagogical research on active learning methods through experimentation. Further, this study contributes to the literature on the impacts of classroom games, particularly in environmental economics.

Appendix A: Appendix Tables and Figures for Chapter 1

Table A1. Summer School Invitation Criteria

	K	1	2	3	4	5	6	7	8	High School
Remote Attendance/Completion	X	X								
Incomplete Reading Grade			X	X	X	X				
Incomplete Math Grade			X	X	X	X				
iReady, Reading		X	X	X	X	X	X	X	X	
iReady, Math		X	X	X	X	X	X	X	X	
Failed Course							X	X	X	X
Incomplete Course							X	X	X	X
World Language							X	X	X	
Acceleration										X
Teacher Recommendation	X	X	X	X	X	X	X	X	X	X
Retention Consideration	X	X	X	X	X	X	X	X	X	
Adapted Curriculum	X	X	X	X	X	X	X	X	X	X

Notes. Students could opt in for the summer program in all grade levels.

Table A2. Summer School Invitation and Participation by Grade Level

	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8	Total
Eligible and Attended	539	801	795	791	709	440	474	489	5,038
Eligible and Not Attended	2,741	2,798	2,714	3,011	3,251	3,389	3,315	3,212	24,431
Not Eligible and Attended	276	68	47	51	42	48	74	87	693
Not Eligible and Not Attended	2,444	2,474	2,841	2,604	2,754	3,022	3,069	3,415	22,623
Total	6,000	6,141	6,379	6,457	6,756	6,899	6,932	7,203	52,785

Table A3. Test of Observed Covariates

Main Specification, Math	0.250	-0.511
	(0.599)	(0.576)
Main Specification, Reading	1.405	-0.476
	(1.334)	(1.171)
Controls		X

Notes. Standard errors in parentheses. Controls used include gender, FRPM eligibility, and ELL status.

Table A4. Test for Balance of Covariates

	Coefficient	Standard Error	P > |z|
FRPM Eligible	-0.012	0.015	0.433
Female	0.002	0.014	0.891
English Language Learner	0.006	0.004	0.137
Black	-0.017	0.140	0.216
Hispanic	0.007	0.009	0.481

Notes. The characteristics in the table represent dummy variables where belonging to the group yields a result of 1 and not belonging yields a result of 0.

Table A5. Density Test for Manipulation

	T	P > |T|
Equal Density	-0.467	0.641

Table A6. RD Results Using Alternative Bandwidths

	Math	Reading
Original Specification	0.250	1.405
	(0.599)	(1.334)
Larger Bandwidth	-0.348	-1.071
	(0.546)	(1.193)
Smaller Bandwidth	-0.226	-1.894
	(0.705)	(1.681)

Notes. Standard errors in parentheses. The original bandwidths used were 28.4 scale points for math and 23.8 scale points for reading. The alternative bandwidths for math are 35 and 20. The alternative bandwidths for reading are 30 and 15.

Table A7. Polynomial Ordering Test

	Math	Reading
Main Specification	0.250	1.405
	(0.599)	(1.334)
Order 2	-0.114	-1.965
	(0.802)	(1.533)
Bias Correction Order 3	-0.223	-1.590
	(0.799)	(1.513)

Notes. Standard errors in parentheses. Main specification uses an order of 1 and bias correction of order 2.

Table A8. Placebo Test

	Math	Reading
Main specification (0)	0.250	1.405
	(0.599)	(1.334)
Lower Cutoff (-30)	0.825	.752
	(0.801)	(1.527)
Higher Cutoff (+30)	0.915	-1.624
	(.900)	(1.605)

Notes. Standard errors in parentheses.

Figure A1. Winter 2021 Math Scale Score Distribution

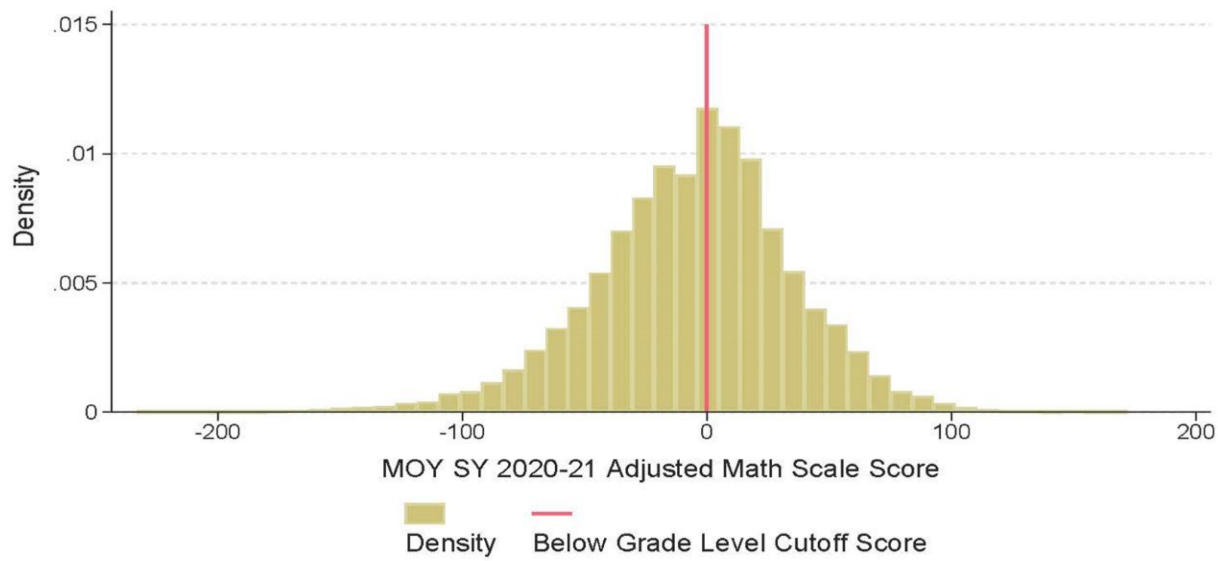


Figure A2. Winter 2021 Reading Scale Score Distribution

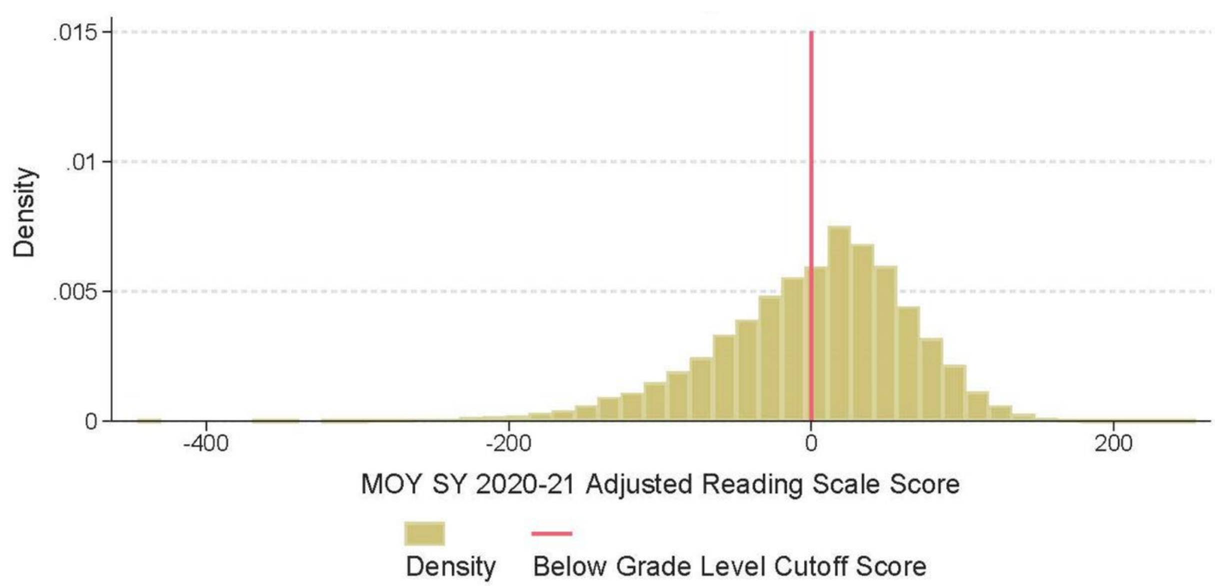


Figure A3. Density Plot

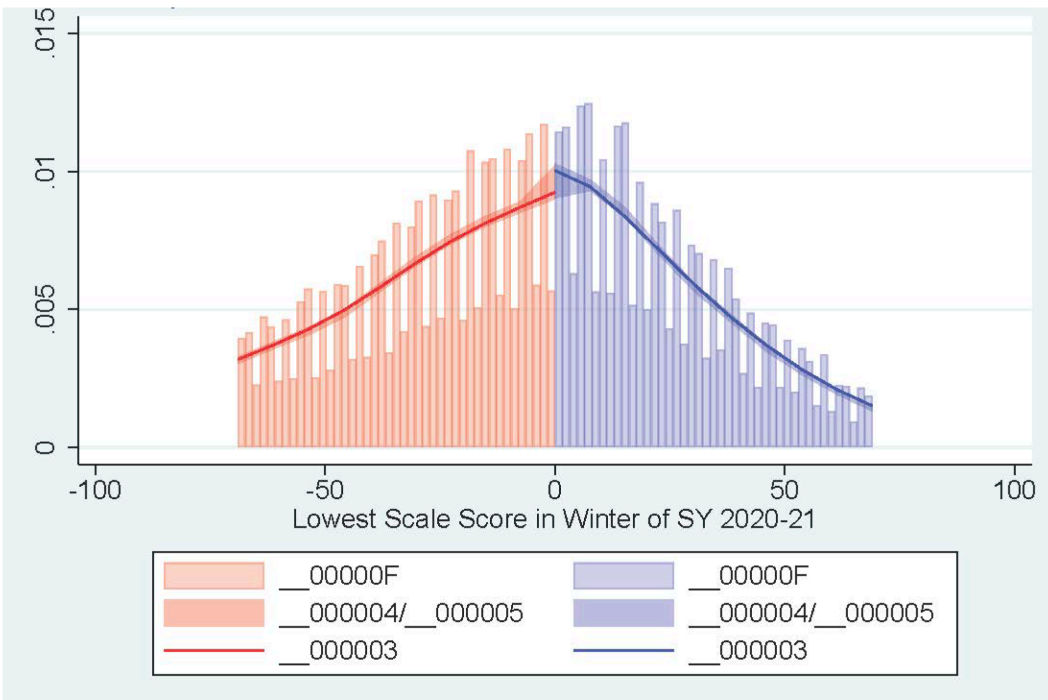


Table A9. Invitation by Criteria for Middle School Students

	Middle Grades
Only invited due to below- grade-level iReady score	9,554 (74.0%)
Only due to course failure	461 (3.6%)
Invited due to both below-grade-level iReady score and course failure	2,905 (22.5%)

Notes. Percentages based on total number of eligible students in grades 6-8.

Appendix B: Appendix Tables for Chapter 2

Table B1. Summary Statistics for Mobility Decisions in District A

Teacher Characteristics	Pre-Pandemic			SY2020			SY2021	
	Stay	Switch	Leave	Stay	Switch	Leave	Stay	Leave
Race/Eth: White	.641	.705	.683	.668	.657	.651	.655	.666
Race/Eth: Black	.245	.200	.224	.223	.234	.248	.227	.238
Race/Eth: Hispanic	.051	.038	.042	.047	.046	.044	.050	.049
Race/Eth: Other	.063	.058	.051	.062	.063	.056	.067	.047
Gender: Female	.825	.768	.814	.814	.768	.809	.802	.806
Gender: Male	.175	.232	.186	.186	.232	.191	.198	.194
Experience: <5 years	.222	.067	.288	.138	.109	.273	.170	.299
Experience: 5-29 years								
Experience: 30+ years	.061	.081	.094	.065	.048	.127	.054	.097
Subject: STEM	.166	.197	.191	.163	.251	.186	.181	.179
Subject: Foreign Language	.055	.046	.054	.053	.047	.053	.052	.040
Subject: Special Education	.047	.039	.054	.043	.032	.049	.043	.062
Subject: Other	.732	.717	.701	.741	.670	.712	.725	.719
Grade Level: Elementary	.467	.337	.436	.441	.297	.421	.413	.431
Grade Level: Middle/High	.533	.663	.564	.559	.703	.579	.587	.569
N	7,285	5,575	3,052	8,588	1,986	1,176	10,545	1,113

Notes. Shown are the breakdowns of teachers making each mobility decision by various teacher characteristics. "Stay" denotes a teacher's decision to continue teaching in their current school in the next school year; "switch" denotes a teacher's decision to switch schools in the district; "leave" denotes a teacher's decision to leave teaching in the district.

Table B2. Summary Statistics for Mobility Decisions in District B

Teacher	Pre-Pandemic				SY2020				SY2021		
Characteristic	Stay	Switch	Move	Leave	Stay	Switch	Move	Leave	Stay	Move	Leave
Race/Eth: White	.275	.223	.239	.295	.254	.226	.300	.325	.260	.246	.238
Race/Eth: Black	.681	.724	.696	.656	.699	.721	.700	.638	.690	.691	.727
Race/Eth: Hispanic	.018	.022	.039	.018	.018	.028	.000	.012	.019	.027	.017
Race/Eth: Other	.027	.030	.026	.031	.029	.025	.000	.025	.031	. 036	.018
Gender: Female	.778	.719	.833	.771	.774	.752	.817	.772	.773	.700	.773
Gender: Male	.222	.231	.167	.229	.226	.248	.183	.228	.227	.300	.227
Experience: <5 years	.180	.101	.266	.325	.136	.112	.207	.247	.141	.184	.273
Experience: 5-29 years	.745	.820	.734	.584							
Experience: 30+ years	.075	.079	.000	.091	.074	.053	.017	.167	.066	.000	.091
Subject: STEM	.138	.214	.147	.186	.143	.198	.200	.190	.145	.155	.160
Subject: Foreign Language	.064	.085	.049	.059	.071	.081	.100	.046	.071	.082	.057
Subject: Special Education	.178	.068	.111	.118	.175	.074	.117	.122	.182	.064	.128
Subject: Other	.621	.633	.693	.637	.612	.647	.583	.642	.602	.700	.655
Grade Level: Elementary	.297	.174	.409	.321	.270	.180	.300	.319	.260	.264	.273
Grade Level: Middle/High	.703	.826	.592	.679	.730	.820	.700	.681	.740	.736	.727
N	6,306	1,621	306	2,018	6,398	323	60	517	6,268	110	774

Notes. Shown are the breakdowns of teachers making each mobility decision by various teacher characteristics. “Stay” denotes a teacher’s decision to continue teaching in their current school in the next school year; “switch” denotes a teacher’s decision to switch schools in the district; “move” denotes a teacher’s decision to move to another school district in Georgia; “leave” denotes a teacher’s decision to leave teaching in Georgia.

Appendix C: Appendix Tables for Chapter 3

Table C1.1. Descriptive Statistics of Participant Demographic Characteristics

	Took only 1st survey, control group	Took only 1st survey, treatment group	Took both surveys, control group	Took both surveys, treatment group	Business School
Female	0.60	0.51	0.63	0.58	0.48
Male	0.40	0.47	0.37	0.39	0.52
Black	0.31	0.36	0.28	0.30	0.41
White	0.23	0.26	0.14	0.27	0.18
Asian	0.31	0.26	0.44	0.31	0.21
Other Race	0.15	0.12	0.15	0.13	0.07
Hispanic	0.17	0.16	0.09	0.20	0.14
Not Hispanic	0.83	0.84	0.91	0.80	0.89
N	181	199	57	104	

Table C1.2. Reported Family Income of Participants

	Took only 1st survey, control group	Took only 1st survey, treatment group	Took both surveys, control group	Took both surveys, treatment group
Lower Class	0.04	0.03	0.05	0.03
Working Class	0.27	0.25	0.28	0.24
Middle Class	0.46	0.47	0.42	0.47
Upper-Middle Class	0.22	0.23	0.23	0.23
Upper Class	0.02	0.03	0.02	0.03
N	181	199	57	104

Note. Students were asked “If you had to use one of these five commonly-used names to describe your social class, which one would it be?”

Table C1.3. Political Leanings of Participants Regarding Economic Issues

	Took only 1st survey, control group	Took only 1st survey, treatment group	Took both surveys, control group	Took both surveys, treatment group
Very Conservative	0.00	0.02	0.00	0.03
Conservative	0.07	0.09	0.05	0.08
Moderate	0.44	0.33	0.46	0.31
Liberal	0.32	0.33	0.33	0.36
Very Liberal	0.05	0.11	0.02	0.13
Prefer Not to Answer	0.12	0.12	0.14	0.11
N	181	199	57	104

Note. Students were asked "On economic policy matters, which classification fits you best?"

Table C1.4. Political Party of Participants Regarding Environmental Issues

	Took only 1st survey, control group	Took only 1st survey, treatment group	Took both surveys, control group	Took both surveys, treatment group
Republican	0.04	0.06	0.05	0.04
Democrat	0.49	0.44	0.47	0.43
Independent	0.07	0.06	0.07	0.07
Other	0.10	0.12	0.04	0.14
Unsure or Prefer not to answer	0.30	0.32	0.37	0.30
N	181	199	57	104

Notes. Students were asked "what political party do you align the most with on environmental policy?" Additional options included "Libertarian" and "Green" but those are included with "Other" in this table due to a low number of students choosing those options.

Table C1.5. Likelihood of Voting in 2022 Midterm Election

	Took only 1st survey, control group	Took only 1st survey, treatment group	Took both surveys, control group	Took both surveys, treatment group
Intend to Vote	0.54	0.49	0.56	0.55
Not Registered but Intend to Vote	0.05	0.08	0.03	0.12
Registered but Does not Intend to Vote	0.08	0.07	0.06	0.05
Not Registered, Does not Intend to Vote	0.16	0.15	0.15	0.13
Unsure	0.08	0.14	0.08	0.08
Prefer not to Answer	0.08	0.07	0.11	0.07
N	181	199	57	104

Note. The question asked on the initial survey was "do you intend to vote in the 2022 election?." Initial survey was given prior to the 2022 midterm election. Answers reflect the registration status and likelihood of voting reported by students at the time of the survey. Information is unavailable regarding whether a student was actually registered at the time of the election or if they actually voted in the election.

Table C2. Student Scores on Cap-and-Trade Quiz

	Pre-game	Post-game	Difference	N
Control	5.105263 (1.739091)	4.333333 (2.182179)	-.7719298 (2.291425)	57
Treatment	4.378641 (1.788397)	4.281553 (2.111674)	-.1442308 (2.082839)	103

Note. Average scores on the cap-and-trade quiz questions. Pre-game and post-game denote average scores on the first and second surveys respectively for students who took both surveys. Difference denotes the average of the differences taken between individual student scores on the two tests and is only shown for students who took both surveys. Standard deviations given in parentheses.

Table C3. Regression Results for Student Cap-and-Trade Quiz Scores

	Pre-game	Post-game	Difference
Assigned to Play Game	-0.874*** (0.306)	-0.282 (0.386)	0.592 (0.402)
Female	-1.177*** (0.330)	-0.194 (0.416)	0.984** (0.433)
Race: Black	0.023 (0.428)	-0.704 (0.541)	-0.726 (0.563
Race: Asian	-0.797* (0.411)	-1.077** (0.519)	-0.280 (0.540)
Race: Other	0.106 (0.512)	-0.870 (0.647)	-0.977 (0.674)
Working Class	-1.981** (0.742)	-0.144 (0.951)	1.837* (0.990)
Middle Class	-1.072 (0.742)	0.921 (0.937)	1.993** (0.976)
Upper-Middle Class	-0.587 (0.782)	0.357 (0.988)	0.944 (1.928)
Upper Class	-0.665 (1.506)	0.511 (1.903)	1.176 (1.981)
Environmental Attitudes	Yes	Yes	Yes
Voting Status	Yes	Yes	Yes
Political Leanings	Yes	Yes	Yes
N	143	143	143

Note. Standard errors in parentheses. The “Difference” regression uses the outcome variable of the change in scores between the second questionnaire and the first questionnaire.

Table C4. Student Scores on Environmental Attitudes Questionnaire

	Pre-game	Post-game	Difference	N
Control	65.52632 (12.14658)	65.64815 (11.16794)	-.0740741 (8.460456)	54
Treatment	66.88235 (10.20415)	65.82 (12.23208)	-.6565657 (9.258379)	99

Note. Average scores on the environmental attitudes questions. Pre-game and post-game denote average scores on the first and second surveys respectively for students who took both surveys. Difference denotes the average of the differences taken between individual student scores on the two tests and is only shown for students who took both surveys. Standard deviations given in parentheses.

Table C5. Regression Results for Environmental Attitude Scores

	Pre-game	Post-game	Difference
Assigned to Play Game	0.691 (1.708)	-0.278 (2.014)	-0.579 (1.808)
Female	5.727*** (1.766)	8.967*** (2.109)	2.957 (1.895)
Race: Black	-7.293*** (2.300)	-8.640*** (2.713)	-1.351 (2.433)
Race: Asian	-1.347 (2.295)	0.561 (2.655)	2.693 (2.397)
Race: Other	-4.997* (2.828)	-3.057 (3.263)	1.893 (2.931)
Pol. Party: Democrat	-2.113 (2.177)	-1.349 (2.563)	1.648 (2.329)
Pol. Party: Green	1.781 (3.458)	1.453 (4.139)	0.272 (3.708)
Pol. Party: Other	-9.599*** (2.800)	-6.206* (3.249)	3.560 (2.915)
Family Income	Yes	Yes	Yes
Voting Status	Yes	Yes	Yes
N	143	143	143

Note. Standard errors in parentheses. The "Difference" regression uses the outcome variable of the change in scores between the second questionnaire and the first questionnaire.

Table C6. Student Responses to Class Engagement Questions

	Control		Treatment	
Did you enjoy playing the game?				
Yes	.		68%	
No	.		6%	
Indifferent	.		26%	
I enjoy taking economics courses				
Not at all	5.56%		5%	
A little	7.41%		11%	
A moderate amount	46.30%		43%	
A lot	18.52%		22%	
A great deal	22.22%		19%	
	Pre-game	**post-game**	**pre-game**	**post-game**
I feel that class activities have helped me to understand real world applications of course material				
Not at all	2.38%	3.70%	4.32%	3%
A little	8.93%	5.56%	14.59%	9%
A moderate amount	35.12%	38.89%	37.84%	37%
A lot	36.90%	37.04%	33.51%	34%
A great deal	16.67%	14.81%	9.73%	17%
I feel more engaged in class when my professor is not just lecturing				
Not at all	3.59%	1.85%	5.46%	4%
A little	4.79%	5.56%	10.38%	8%
A moderate amount	37.13%	42.56%	33.88%	24%
A lot	33.53%	33.33%	32.79%	36%
A great deal	20.96%	16.67%	17.49%	28%

Appendix D. Cap-and-Trade Knowledge Questions

Below are the questions that were used in the questionnaire to evaluate student knowledge of cap-and-trade policies. Students were randomly given 10 of the following questions. The answer in **bold** is the correct answer.

Question 1 (Version 1): Which of the following is the best definition of a cap-and-trade policy for pollution?
Answer Choices:
a. Consumption of the good being produced is capped by the government at the current level, but the good can still be traded in the market.
b. Production of the good is capped by the government at the current level, but the good can still be traded in the market.
c. Emissions of a pollutant are capped by the government at the current level, and the good being produced can still be traded in the market
d. **Emissions of a pollutant are capped by the government at a chosen level, and firms are given permits by the government to emit pollutants and have the right to trade these permits.**

Question 1 (Version 2): Which of the following is the best definition of a cap-and-trade policy?
Answer Choices:
a. Consumption of the good being produced is capped by the government at the current level, but the good can still be traded in the market.
b. Production of the good is capped by the government at the current level, but the good can still be traded in the market.
c. Production of an economic bad is capped by the government at the current level, and the good being produced can still be traded in the market
d. **Production of an economic bad is capped by the government at a chosen level, and firms are given permits by the government to emit pollutants and have the right to trade these permits.**

Question 2 (Version 1): What is the key goal of a cap-and-trade policy for pollution?
Answer Choices:
a. Reducing emissions
b. Encouraging firms to produce more goods
c. Destroying a market for a certain product
d. Reducing consumption of a certain good

Question 2 (Version 2): Which of the following is not an aim of a cap-and-trade policy for pollution?
Answer Choices:
a. Reducing emissions
b. Creating a market to trade “rights” to pollute
c. Destroying a market for a certain product
d. Reducing production of a certain good

Question 3 (Version 1): If a cap and trade policy is enacted properly, targeted emissions are ________ and social benefits ________.
Answer Choices:
a. reduced; increase
b. reduced: decrease
c. increased; increase
d. increased; decrease

Question 3 (Version 2): If a cap and trade policy is enacted properly, targeted emissions are ________ and social costs ________.
Answer Choices:
a. reduced; increase
b. reduced: decrease
c. increased; increase
d. increased; decrease

Question 3 (Version 3): When cap-and-trade policies are enacted effectively, what happens to social costs?
Answer Choices:
a. Social costs increase
b. Social costs decrease
c. Social costs stay the same
d. It depends

Question 3 (Version 4): When cap-and-trade policies are enacted effectively, what happens to social benefits?
Answer Choices:
a. Social benefits increase
b. Social benefits decrease
c. Social benefits stay the same
d. It depends

Question 4 (Version 1): How are cap-and-trade policies different from other types of environmental regulation like carbon taxes?
Answer Choices:
a. They aim to reduce emissions
b. They create a market to trade "rights" to pollute
c. They create regulations
d. They increase the price of polluting for producers.

Question 4 (Version 2): Cap-and trade policies differ from command-and control policies in that they ______ . . .
Answer Choices:
a. Dictate technology standards for companies
b. Allow markets to determine the price of a pollutant
c. Do not help jurisdictions to meet a certain emissions target
d. Are not commonly used to lower emissions

Question 4 (Version 3): Cap-and-trade policies are similar to command-and-control policies in that they_____
Answer Choices:
a. Dictate technology standards for companies
b. Allow markets to determine the price of a pollutant
c. Do not help jurisdictions to meet a certain emissions target
d. Are commonly used to lower emissions

Question 5 (Version 1): What is not traditionally "capped" by the government in a cap-and-trade policy for pollution?
Answer Choices:
a. Any economic bad
b. Production of the good whose production emits pollutants
c. Emissions of a pollutant
d. The number of permits issued to producers

Question 5 (Version 2): What can be "capped" by the government in a cap-and-trade policy?
Answer Choices:
a. Goods with positive externalities
b. Only pollution
c. Any economic bad
d. Number of firms producing a good whose production emits pollutants

Question 5 (Version 3): What is traditionally "capped" by the government in a cap-and-trade policy for pollution?
Answer Choices:
a. Consumption of the good whose production emits pollutants
b. Production of the good whose production emits pollutants
c. **Emissions of a pollutant**
d. Number of firms producing a good whose production emits pollutants

Question 6 (Version 1): An externality is defined as
Answer Choices:
a. a cost or benefit that arises from production and falls on someone other than the producer, or a cost or benefit that arises from consumption and falls on someone other than the consumer.
b. an additional cost imposed by the government on producers
c. an additional gain received by consumers from decisions made by the government.
d. the additional amount consumers have to pay to consume an additional amount of a good or service.

Question 7 (Version 1): Production that releases emissions creates a ________ externality.
Answer Choices:
a. negative consumption
b. positive consumption
c. negative production
d. positive production

Question 7 (Version 2): Air pollution generated by a paper mill factory is an example of a
Answer Choices:
a. positive production externality
b. negative production externality
c. positive consumption externality
d. negative consumption externality

Question 8 (Version 1): Which one of the following attributes does not apply to a system of tradable permits?
Answer Choices:
a. The price of permits is set by a government
b. Permits promote cost-effective emissions reductions
c. Permits can be traded in an open market.
d. The number of permits are set by a government

Question 9 (Version 1): What is the main advantage of a system of tradable permits relative to a carbon tax?
Answer Choices:
a. It encourages technological innovation.
b. The level of total emissions is known with certainty.
c. It results in a lower level of price increases to consumers.
d. The price of permits is known with certainty.

Appendix E. Attitudes towards Environmental Policy Questionnaire and Demographic Survey

Survey Questions			
Question Stem	Items	Response Scale	Question Source
In the next 30 years, how certain are you that changes in the climate will have a negative impact on..	You and your family Your town and your city Your state People across the world	5-point Likert, labeled "Not at all," "A little," "Somewhat," "very," or "Extremely"	Adapted from Howe et al. (2015)
Thinking of life in your town or city, to the best of your knowledge, how much of an impact will a changing climate have on…	Drought or water shortages Higher likelihood of storms and floods Higher severity of storms and floods Increased likelihood of heatwaves	5-point Likert, labeled "No impact," "A small impact," "A moderate impact," "A large impact" or "An extremely large impact"	Adapted from Howe et al. (2015)
For the following statements regarding the environment and society. Please indicate how much you agree or disagree with each statement.	We are approaching the limit of the number of people the earth can support. The balance of nature is very delicate and easily upset. Despite our special abilities to adapt, humans are still subject to the laws of nature. If things continue with their present course, we will soon experience a major ecological catastrophe.	5-point Likert, labeled "Strongly disagree," "Mildly disagree," "Neutral," "Mildly agree" or "Strongly agree"	Four-Item version of the NEP questionnaire (Lopez-Bonilla and Lopez-Bonilla 2016)

In your opinion, how often can…	The federal government in Washington D.C. be trusted to do what is right Your town or city government be trusted to do what is right	5-point Likert, labeled "Never," "Rarely," "Sometimes," "Very often" or "Extremely often"	American National Election Studies (2016) survey

Demographic Questions

Please enter your age.*	Open response question
What is your gender?*	"Female," "Male," "Non-binary," or "Prefer not to answer"
Do you consider yourself to be Hispanic, Latino(a), or Chicano(a)?*	"Yes" and "No"
What racial or ethnic groups do you identify with? Please check all that apply.*	"White," "Black or African American," "Asian," "American Indian or Alaska Native," "Native Hawaiian or Other Pacific Islander," "Race not listed," and "Prefer not to say."
What is your hometown?*	Open response question
What is your major?*	Open response question
What political party do you align the most with on environmental policy?	"Republican," "Democrat," "Green Party," "Independent," "Libertarian," "Other," "Unsure," or "Prefer not to answer"
On economic policy matters, which classification fits you best?	"Very conservative," "Conservative," "Moderate," "Liberal," "Very Liberal," or "Prefer not to answer"

If you had to use one of these five commonly-used names to describe your social class, which one would it be?*	“Lower class or poor,” “Working class,” “Middle class,” “Upper middle class,” “Upper class,” or “Prefer not to answer”
Do you intend to vote in the 2022 election?	“Yes,” “No, but I am registered,” “I am not currently registered but I am planning on registering,” “No, I am not registered,” “I am not sure,” or “Prefer not to answer”

Classroom Involvement Attitude Questions		
Did you enjoy playing the game?**		“Yes,” “No”, or “Indifferent”
I enjoy taking economics courses.		"Female," "Male," "Non-binary," or "Prefer not to answer"
For the following statements please indicate how much you agree or disagree with each statement.	I enjoy taking economics courses. I feel that class activities have helped me understand real world applications of course material. I feel more engaged in class when my professor is not just lecturing.	"Not at all," “A little,” “A moderate amount,” “A lot,” or “A great deal”

* Indicates questions only included in the pre-survey
** Indicates a question only included for the post game survey for treated groups.

Appendix F. Cap-and-Trade Game Instructions

Below are the instructions used to play the game. These have been modified from the original instructions given in the "For Want of a Chair" paper.

All instructions will be given to students verbally with the classroom projector screen being used to aid students with moving through the game. Images shown are actual screenshots from the game software.

1. Students will be given a brief overview of cap-and-trade policies.

2. Students will be shown a demonstration of how the game works by the experimenter.

3. The experimenter will determine the number of "chairs" in play and students will be shown the number and their current social costs and benefits on the screen, as shown below. Students will then enter the game and be randomly assigned a chair or no chair.

There are 3 chairs in play

Private Benefits	Social Costs	Net Social Benefits
$ 17376	$ 765	$ 16611

4. Students will see their profit with a chair, without a chair, and the difference, as shown in the below examples. They will also see whether or not they have a chair. At this point, they will determine whether they want to try to trade and for how much.

In this session, your profit with a chair will be $ 3869

Your profit without a chair will be $ 1081

The difference is $ 2788

items ID 4

1 

SELL

other | offer | $

In this session, your profit with a chair will be $ 5295

Your profit without a chair will be $ 4512

The difference is $ 783

items ID 3

no items

BUY

other | offer | $

5. Students will physically move around the room to attempt to make trades with other students. They will have approximately 2 minutes to do this. If a student finds another student with whom they would like to trade, both students will enter the trade amount and other student's game ID into their individual devices.

6. As students engage in trades, the trades will show up on the screen in the classroom as shown below. This does not say who engaged in a trade or how much the traders valued the chair, simply that a trade occurred and for how much.

round 1 chart on average prediction

	time		seller	Price in $
1	16:54:35	390843	390842	1000

7. The game will conclude with students seeing a comparison of social cost and benefit before and after trading, shown below, to demonstrate how cap-and-trade policies can be effective.

	Private Benefits	Social Costs	Net Social Benefits
Before Trading	$ 17376	$ 765	$ 16611
After Trading	$ 19381	$ 765	$ 18616

8. As time allows, the game may be repeated with different numbers of chairs.

Appendix G. Informed Consent

Georgia State University
Informed Consent

Title: Understanding Cap and Trade Game
Principal Investigator: Stefano Carattini
Student Principal Investigator: Sarah Barry
Co-Investigator: Caroline Lamprecht

Procedures
You are being asked to take part in a research study. If you decide to participate, you will complete two questionnaires which ask basic information about yourself and questions on environmental policy. These surveys will be administered online. Each survey should take approximately 10 minutes to complete. Further, you may be asked to participate in a game during one of your regular classes which will take approximately 30 minutes. This game will involve the use of technology (a personal computer or smartphone) as well as face-to-face interaction with students in your class to make economic decisions. The game will be led by a graduate student researcher.

Compensation
You will receive extra credit in one of your courses for participating in this study. The exact amount will be up to your instructor but will be approximately 5 extra credit points on an exam. The course in which you will receive credit will be the one mentioned in your recruitment email or for the instructor who sends you information on this study. If you do not wish to participate in the study, your instructor will provide an alternative assignment.

Voluntary Participation and Withdrawal
You do not have to be in this study. You may skip questions or stop participating at any time. Not participating or stopping participation will have no impact on your course grades.

Contact Information
Contact Stefano Carattini or Sarah Barry at sbarry8@gsu.edu

Consent
If you are willing to volunteer for this research, please start the survey.

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Vita

Sarah Sterling King was raised in Richmond Hill, Georgia. After graduating from Richmond Hill High School in 2014, she attended Mercer University in Macon, Georgia. She graduated Magna Cum Laude and with University Honors in 2018 with a BA in Economics and Mathematics and a minor in Psychology.

In the fall of 2018, Sarah began her doctoral studies in Economics at Georgia State University in Atlanta, Georgia. While at Georgia State, she worked as a Graduate Research Assistant with the Experimental Economics Center (2018-2020) and the Georgia Policy Labs (2020-2023); she was the instructor of record for three undergraduate economics courses including two principles-level courses and one upper-level course in urban economics; and she was a member of the DEI Core Team for the Georgia Policy Labs.

Sarah has coauthored multiple policy reports through GPL; has coauthored a paper relating to engagement during pandemic-related virtual learning; and has received many teaching certifications and research awards including the Second Century Initiative (2CI) University Fellowship and the Outstanding Oral Presentation Award at the inaugural Graduate Research Conference at Georgia State. Her research interests include education policy, labor economics, experimental economics, urban economics, and economics pedagogy.

Sarah has accepted a faculty position as a lecturer in the Department of Economics at Christopher Newport University in Newport News, Virginia.