Summer 8-8-2023

Three Essays on Education and Health Policy for K-12 Students and Young Adults

Sungmee Kim

ABSTRACT

THREE ESSAYS ON EDUCATION AND HEALTH POLICY FOR K-12 STUDENTS AND YOUNG ADULTS

BY

SUNGMEE KIM

August, 2023

Committee Chair: Dr. Tim Sass

Major Department: Economics

Three essays of this dissertation explore the impact of policies and shocks on education and health outcome of K-12 students and young adults.

Chapter 1 documents the gender achievement gap and gender difference in remote learning, exploiting differential exposure to remote learning induced by the COVID-19 pandemic. Using longitudinal administrative data of a school district in Georgia and employing Blinder-Oaxaca decomposition method, I find that exposure to disruptive peers in classroom and a lack of self-control generally have a detrimental effect on students' academic performance. Moreover, gender achievement gaps in both math and reading widen, favoring girls, over the course of the pandemic and the pandemic-induced shift to remote learning where gender-based impact differences in exposure to remote learning and proportion of disruptive peers in classroom explain considerable share of the gender gaps.

Chapter 2 estimates the impact of the universal gaming shutdown policy in South Korea. The analyses utilize 7-year panel data obtained from the Korean Children and Youth Panel Survey and employ a difference-in-differences method. Exploring heterogeneous effects of the policy based on students' pre-policy gaming pattern, I find that heavy gamers decreased their

gaming hours by 26 percent of the pre-policy mean. The findings also suggest that the policy reduced the intensity of computer game usage and cellphone game usage among individuals who were heavy gamers.

Lastly, chapter 3 investigates the impact of the Affordable Care Act (ACA) Medicaid expansion on young adults falling in a “coverage gap”. Utilizing the March Current Population Survey (CPS) and employing the difference-in-differences method, the results indicate that the ACA Medicaid expansion had a positive impact on the health insurance coverage rate of poor young adults who fell within the Medicaid coverage gap. In particular, young adults in expansion states experienced a significant increase in Medicaid coverage rate and a decrease in uninsured rate compared to those in non-expansion states. Moreover, the event study results suggest a gradual increase in Medicaid coverage rates and decrease in uninsured rate among young adults in expansion states in the years following the implementation of the expansion.

THREE ESSAYS ON EDUCATION AND HEALTH POLICY FOR K-12 STUDENTS AND YOUNG ADULTS

BY

SUNGMEE KIM

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY
2023

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.

Dissertation Chair: Dr. Tim Sass

Committee: Dr. Haeil Jung
Dr. Daniel Kreisman
Dr. James Marton

Electronic Version Approved:

Ann-Margaret Esnard, Interim Dean
Andrew Young School of Policy Studies
Georgia State University
August, 2023

Dedication

I dedicate this dissertation to my family, my friends, and Jongtaek. It is your love and support that have shaped the person I am today, and I would have not reached this significant milestone in my life if it were not for you. May this dissertation shed light on the path towards my future endeavors.

Acknowledgements

This dissertation is a product of the collective support and contributions from many individuals.

First, I express my deepest gratitude to my advisor, Dr. Tim Sass, for his invaluable guidance and unwavering support throughout my Ph.D. journey. I still remember the day I received my first work email from Tim– it was a moment that will forever stay with me.

I extend my sincere thanks to Dr. James Marton, Dr. Daniel Kreisman, and Dr. Haeil Jung for their valuable feedback as members of my dissertation committee. Their contributions have been instrumental in shaping my research, and I sincerely appreciate their dedication and encouragement.

For chapter 1, I am grateful to the Georgia Policy Labs and their partner school districts for providing me the data for the research. I also thank Dr. Daniel Lee and attendees at GSU seminars, GCSU presentation, and the poster session of ASSA 2023 Annual Meeting for their feedback and support. For chapter 2, I appreciate the opportunity to access and utilize the student panel data provided by the National Youth Policy Institute of South Korea.

This dissertation is generously supported by Dan E. Sweat Dissertation Fellowship at Georgia State University.

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Chapter 1: Gender Differences in Remote Learning amid COVID-19: Disruptive Peers and Self-Control

1.1 Introduction

Two years after the COVID-19 pandemic broke out, concerns over short-term and long-term impacts of learning disruption have remained prevalent among education experts. A recent release of the National Assessment of Educational Progress (NAEP) long-term trend assessment results confirms these concerns; there were unprecedented declines in both reading and math assessment scores from 2020 to 2022, erasing two decades of academic progress in reading and mathematics (National Center for Education Statistics, 2022). This decline is the largest in the average reading score since 1990, and the first-ever score decline in mathematics. Not only has the pandemic had tremendous effects on students' educational performance, there are also concerns that it might have exacerbated pre-existent achievement gaps by race/ethnicity, gender, and socio-economic status (Skar et al., 2021; Bacher-Hicks et al., 2022; Aucejo et al., 2020; Copeland et al., 2021; Bailey et al., 2021; Donnelly & Patrinos, 2021; Dorn et al., 2020; Hammerstein et al., 2021; Kuhfeld et al., 2022). A consensus from the existing literature is that achievement gaps between students from different subgroups have widened over the course of the pandemic. For example, Kuhfeld et al. (2022) reports that achievement gaps between students in low-poverty and high-poverty elementary schools grew by 0.1 - 0.2 standard deviations, primarily during school year (SY) 2020-21. Engzell et al. (2021) documents the effect of school closures during the pandemic on Dutch students aged 8 to 11 and suggests learning loss was most pronounced among students from disadvantaged homes. It is troubling that widened achievement gaps resulting from the pandemic could potentially leave a "lasting legacy" to students' future outcomes as well as translate into larger achievement gaps in later years, if students were affected in their earlier ages (Werner & Woessmann, 2022; Autor et al., 2020).

When the COVID-19 virus started to spread in early 2020, schools around the world responded by closing their buildings and serving students remotely for the remainder of SY 2019-20, which changed the nature of the student learning environment (UNESCO Institute for Statistics, 2021). Compared to a traditional face-to-face learning environment, the pandemic-induced remote learning has likely altered the way that a combination of educational inputs – including student/family inputs, peer inputs, and school/teacher inputs – interact and affect student achievement. For instance, there had been fewer direct peer interactions and interactions between teachers and students, which would result in less exposure to misbehaving peers and teachers' supervision. Such changes in the relative importance of educational inputs during remote learning could be potential mechanisms that might explain widened achievement gaps across various student subgroups, given the evidence from the literature that the amount of exposure to each educational input, and the magnitude of impacts of those inputs differ across student subgroups (Krein & Beller, 1988; Dahl & Lochner, 2005; Autor et al., 2020).

This paper was initially motivated by early findings from the Georgia Policy Labs, where the authors find that female students in metro-Atlanta school districts fared better than male students during remote learning, in terms of both reading and math formative assessment scores (Sass and Goldring, 2021). While there are several studies documenting the possible impacts of pandemic-related learning disruption on various student subgroups, relatively less is known about the causal impact of pandemic-induced change in learning environment on gender-based differences in student achievement growth. Although there are a number of ways to potentially explain the observed gender learning gap, I focus on two possible mechanisms - classroom peer composition and students' own self-control. Disruptive-peer effects and innate/extrinsic self-control level vary by student gender and potentially induce changes in achievement gaps between boys and girls (Zimmerman, 2003; Duckworth & Seligman, 2006; Han & Li, 2009; Ficano, 2012; Duckworth et al., 2015; Carrell et al., 2018). Moreover, there has been a growing strand of literature on the role of non-cognitive skills and peers as sources of gender gaps as well as factors determining student outcomes (Jacob, 2002; Bertrand & Pan, 2013; Nakajima et al., 2020). Based on the pandemic-induced shifts in learning environment and the evidence from the existing literature, I propose two hypotheses as potential explanations for the observed gender achievement gaps in the districts I study here: (i) remote instruction changed the nature of peer interactions and girls were less disrupted by their mis-behaving peers during remote learning after school closures in mid-March of 2020, and (ii) girls are better at self-control, which is an essential component of success in remote learning, and thus learned more than boys did when schools were closed. As the potential mechanisms may have long-term consequences for boys' and girls' learning trajectories and progressions in the future, gender differences in achievement are a matter of considerable concern (OECD, 2019).

The central questions in this paper are: (i) what were the pre-pandemic relationship s between proportion of disruptive peers & self-control level and achievement? (ii) to what extent do student self-control and proportion of disruptive peers explain the observed gender achievement gaps over the course of the pandemic? (iii) did any observed gender differences in student outcomes during the remote learning diminish for students who returned to in-person learning in fall of SY 2020-21? I examine these questions by utilizing administrative datasets of a metro-Atlanta school district and exploiting the variation in the intensity of classroom disruptiveness, self-control level, and the proportion of instructional remote learning days by gender.[1] In order to explore the trend in the gender achievement gaps and estimate the change in the magnitude of impacts of the two key mechanisms across gender over the course of the pandemic, I use the Blinder-Oaxaca decomposition method, where I estimate empirical models separately for female and male student groups and investigate whether changes in gender achievement gaps during the pandemic-induced remote learning stemmed from the two mechanisms of interest.

The rest of the paper is organized as follows: Section 2, comprised of two subsections, presents contextual information. The first subsection provides information on school closures and return to in-person learning in Georgia and the particular school district I study in this paper. The second subsection documents student achievement and preexisting gender achievement gaps in the district. A conceptual framework for the study, which is based on a traditional cumulative achievement production function, and methodology for the empirical analyses are presented in Section 3. Section 4 provides results of the analyses, and the last section discusses the implications of the findings and concludes.

1.2 Background

1.2.1 School Closure and Return to In-Person Learning in Metro-Atlanta School Districts

Due to the impact of COVID-19, Governor Brian P. Kemp issued an Executive Order on March 14, 2020 to close all public elementary, secondary, and post-secondary schools in Georgia from March 18, 2020 through March 31, 2020 and accordingly students were offered remote learning (Lane, 2020; Sass & Goldring, 2021). Another executive order was signed on March 26 of the same year to extend the school closure through April 24, 2020, and a week later the

[1] Distribution of exposure to remote instruction by gender is presented in Figure 1.4.

Governor announced all K-12 public schools would remain closed for the remainder of school year (SY) 2019-20 (Georgia Department of Education, 2020).

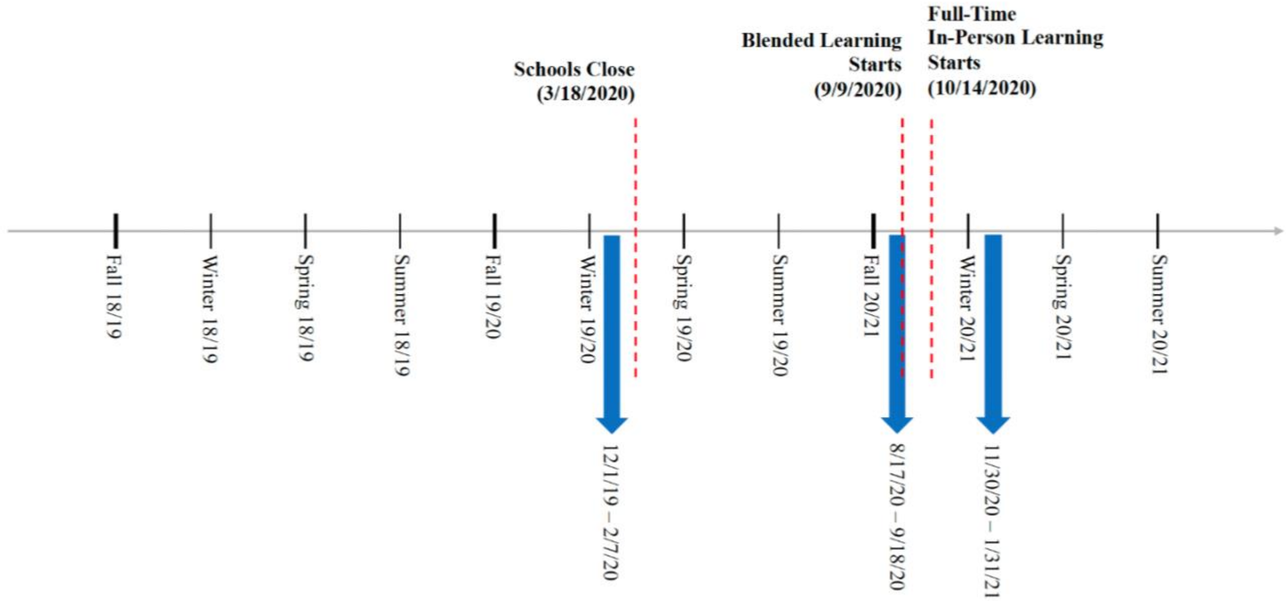
After the school closures in March 2020, most school districts in metro Atlanta began SY 2020-2021 with fully remote instruction but started to offer parents a choice of in-person instruction for their child at varying times in SY 2020-21. The school district I study chose a "phased" approach for returning to face-to-face instruction during the fall of SY 2020-21. Table 1.1 and Figure 1.1 present a timeline of phases and actual timing of return to fulltime in-person instruction in the district. Each phase was implemented based on the district's school reopening plan matrix before the district fully switched to offering full-time face-to-face learning on October 14, 2020.[2] Until the first phase (Phase I) began on September 9, 2020, remote learning was provided to all students. Given that the school year typically begins in early August, Phase I started about a month after the school year began. During Phase I, students in Pre-K through 2 were given a voluntary opportunity to receive a 90-minute in-person instruction and support session once per week. During this phase, students in grades 3-12 were given the option to receive such support by scheduling 1-on-1 meetings with their teachers, while continuing their Universal Remote Learning schedule as planned. Meals or snacks were provided during this phase and transportation was provided for Pre-K through second grade students attending a once-a-week in-person session[3]. Based on the district's school reopening plan, the district skipped Phase II and implemented Phase III weeks after the first phase began. Phase III and the rest of the phases were implemented for all students through the rest of the fall semester ending December 18, 2020.

[2] Details on the district's school reopening plan matrix are tabulated in Appendix A1.
[3] Transportation was provided for students in grades 3-5 and all middle/high school students returning for face-to-face instruction during future phases.

Table 1.1. Phase and Actual Timing of Return to Full-Time In-Person Instruction in the District

Phases	Learning Mode	Actual Start Date
Universal Remote Learning	All remote	First day of school (August 17, 2020)
Phase I	90-minute session, once a week (Pre-K–2), 1:1 meeting by appointment (3–12)	September 9, 2020
Phase II	1 half-day face-to-face per week	N/A
Phase III	1 full-day face-to-face per week	September 21, 2020
Phase IV	2 full days face-to-face per week	October 5, 2020
Phase V	Full-time face-to-face or remote	October 14, 2020

Figure 1.1. Timeline of School Closure and iReady Diagnostic Testing Windows



Before Phase III began on September 21, 2020, a first round of parental survey was conducted to gather information on parents' preference on children's learning mode (in-person or remote) and mode of transportation to/from school for the rest of the phases. Parents and/or guardians were required to select an option for each child between September 14 through 18. If a parent/guardian had not made a selection for each of their children by the end of the survey period, the default selection would be face-to-face. While parents/guardians were encouraged to make a semester-long commitment through December 18, parents and guardians were able to retake the survey as long as the final decision was made by September 18. Students in grades 2 through 12 received a device issued by the school district and meals were provided at no charge for all students. Schools in the district had a thorough plan to meet the parents' desire to stay remote or have their children receive instruction face-to-face, so there seemed to be little-to-no institutional constraint on the provision of desired learning mode. In Phase III students could receive one full day of in-person instruction per week.

In Phase IV (which started on October 5), two full days of in-person instruction, were provided for all students who did not select fully-remote instruction. Finally, on October 14, 2020, schools fully re-opened for in-person instruction and students could either receive face-to-face instruction five days a week or remain in full-time remote learning.

Although parents and students self-selected into learning modes, two factors contributed some exogenous variation in student exposure to remote learning. First, testing windows for formative assessments are fairly broad, so the dates at which individual students take exams varied widely as tabulated in Tables 1.2 and 1.3. Given the phase-in of in-person learning, this translates into different exposure to remote learning between fall and winter assessments in SY 2020-21. Second, once full-time in-person instruction resumed on October 14, any student who was sick, had a fever, tested positive for COVID-19, or had been exposed to COVID-19 was expected to stay home and follow public health protocols before returning to school. Thus, differences in exposure to COVID-19 generated additional variation in the proportion of time spent in remote learning. This exogenous variation in exposure to remote learning provides an opportunity to compare outcomes of students that underwent distinct changes in instructional mode as well as to investigate whether gender differences in achievement growth varied by learning mode.

Table 1.2. Descriptive Statistics of Testing Window for Fall and Winter Exams, SY 2020-21

		Testing Window	Mean	Median
Math	Fall SY 2020-21	8/24/2020 – 10/23/2020	9/2/2020	9/1/2020
	Winter SY 2020-21	11/30/2020 – 1/31/2021	12/29/2020	1/7/2021
Reading	Fall SY 2020-21	8/24/2020 – 10/23/2020	9/1/2020	8/31/2020
	Winter SY 2020-21	11/30/2020 – 1/30/2021	12/30/2020	1/7/2021

Table 1.3. Number of Attended Days between Fall and Winter Exams, SY 2020-21

	Mean	SD	Min.	Max.
Math	67.29	9.00	22	87
Reading	68.37	9.38	24	87

1.2.2 Gender Achievement Gap in Metro-Atlanta School District

There has been considerable prior research that shows girls on average outperform boys on reading/ELA exams whereas they either perform similarly or girls slightly outperform boys on math exams (Duckworth & Seligman, 2006; Lai, 2010; Sartain et al., 2023; for a meta-analysis: Voyer & Voyer, 2014). In this subsection, I briefly document the pre-existing gender achievement gap in the metro-Atlanta school district I study in this paper. In the district, a formative, adaptive assessment called iReady Diagnostic (produced by Curriculum Associates) is administered every fall and winter of each academic year; I plot standardized iReady math and reading assessment score trends to investigate pre-pandemic gender-based achievement differences in the district[4]. Figures 1.2 and 1.3 present the raw trends of standardized math and reading iReady achievement scores of a pooled sample of students in grades 1 to 8, over the analyses period (SY 2018-19 to SY 2020-21).[5] The three vertical dashed lines in the figures represent the initial school closure, the initiation of blended learning, and the introduction of full-time in-person (or remote) instruction, respectively. As illustrated in the figures, the trends in math and reading achievement for both genders align with empirical evidence from the gender-gap literature, which consistently indicates that girls outperform boys in both subjects, with the disparity being more pronounced in reading. Moreover, the gender-based disparities in both math and reading achievement demonstrate an expanding trajectory subsequent to the initial school closure, where the gaps further widen between the fall and winter of SY 2020-21.

1.3 Methodology

1.3.1 Conceptual Framework

Based on the traditional education production function, there are various inputs that potentially affect student outcomes (student academic achievement, most commonly) such as student input, family input, peer input, school and teacher input, where the function provides direct evidence about the effectiveness of each input and numerous policies that were

[4] For more details on the iReady Diagnostic, visit: https://www.curriculumassociates.com/programs/iready-assessment/diagnostic

[5] I standardized the iReady scale scores by year-semester and grade within the district I study, because information on national means and standard deviations are not publicly available. For the decomposition analyses, I calculate achievement growth per day and use it as a main dependent variable.

implemented based on its estimation (Hanushek, 2020). Following the mathematical presentation of Boardman and Murnane (1979), Hanushek (1979), Todd and Wolpin (2003), and Sass et al. (2014), such relationship can be expressed as a simplified cumulative achievement function:

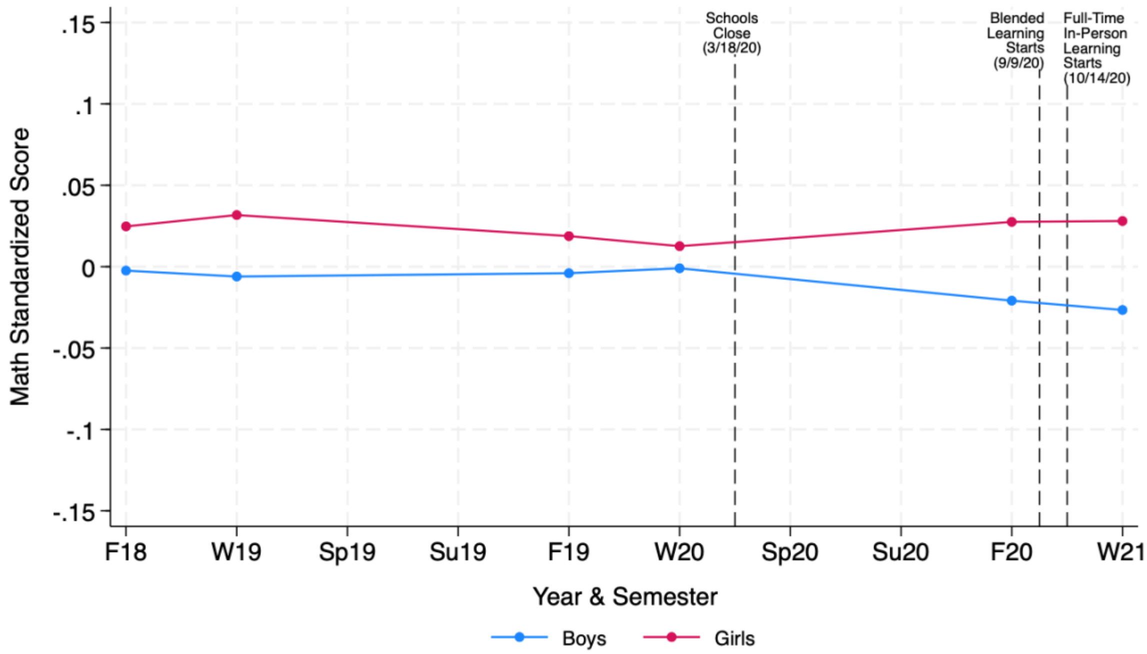
$$A_{it} = f(S_{i(t)}, P_{i(t)}, X_{i(t)}, F_{i(t)}, I_{i0}, \epsilon_{it}) \tag{1.1}$$

where A_{it} is a student i's academic achievement at time t, $S_{i(t)}$ is school-related inputs such as the number of students per school, school characteristics, teacher's experience, teacher's salary, cumulative to time t. Likewise, $P_{i(t)}$ is cumulative peer inputs, such as peers' academic achievement, income and socioeconomic status of peers' parents, peers' disruptiveness, $X_{i(t)}$ is cumulative individual/student inputs such as innate skill endowments, cognitive and non-cognitive skills such as critical thinking, consciousness, and self-discipline, and $F_{i(t)}$ is cumulative family-related inputs such as parents' occupation, parent's education, household income, the number of siblings, and so on. I_{i0} and ϵ_{it} are the student i's endowed innate ability and an idiosyncratic error term at time t. Taking this cumulative achievement function and the history of all inputs in time t and $t - 1$ and rearranging them under several model assumptions produce the following cumulative achievement equation:

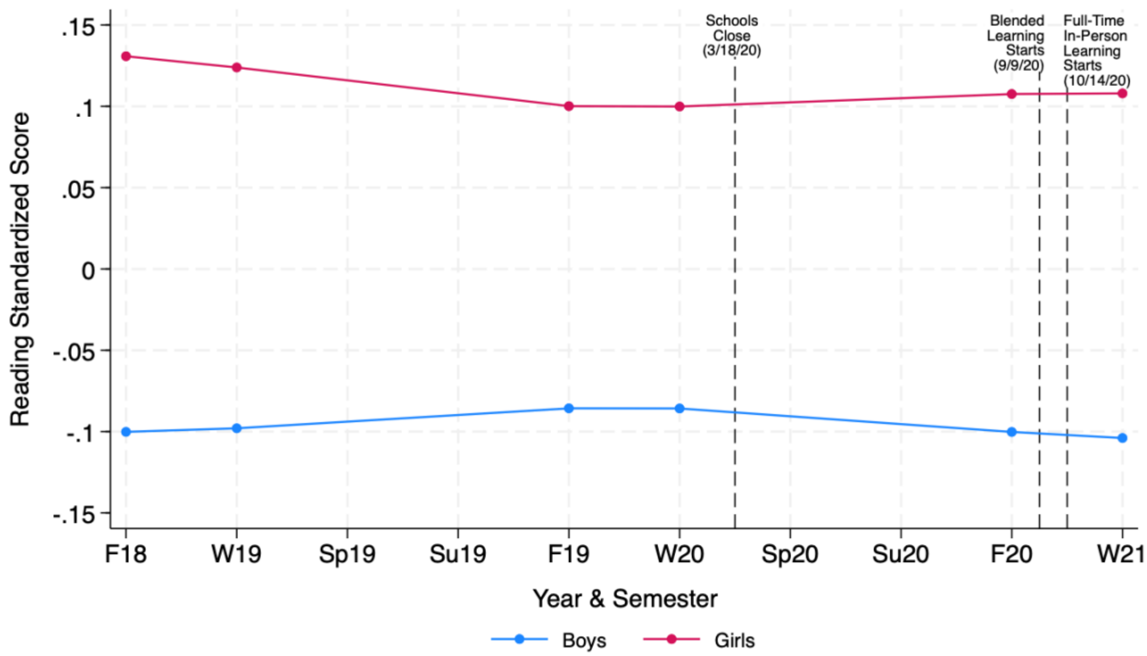
$$A_{igst} = \beta_1 X_{igst} + \beta_2 P_{-igst} + \beta_3 S_{igst} + \theta A_{igst-1} + \rho_i + \lambda_g + \sigma_s + \xi_{igst} \tag{1.2}$$

where A_{igst} is an academic achievement of a student i of grade g, in school s in year-semester t, P_{-igst} is characteristics of the student i's peers, and S_{igst} is time-varying school and teacher inputs. A_{igst-1} is a prior academic achievement of the student, which is assumed to serve as a sufficient statistic for all prior school inputs. ρ_i, λ_g, and σ_s are time-invariant student/family, grade, and school/teacher inputs, respectively. As schools switched their learning mode from traditional face-to-face instruction to remote instruction after the pandemic broke out, the

Figure 1.2. Standardized iReady Assessment Score Trends, SY 2018-19 – SY 2020-21

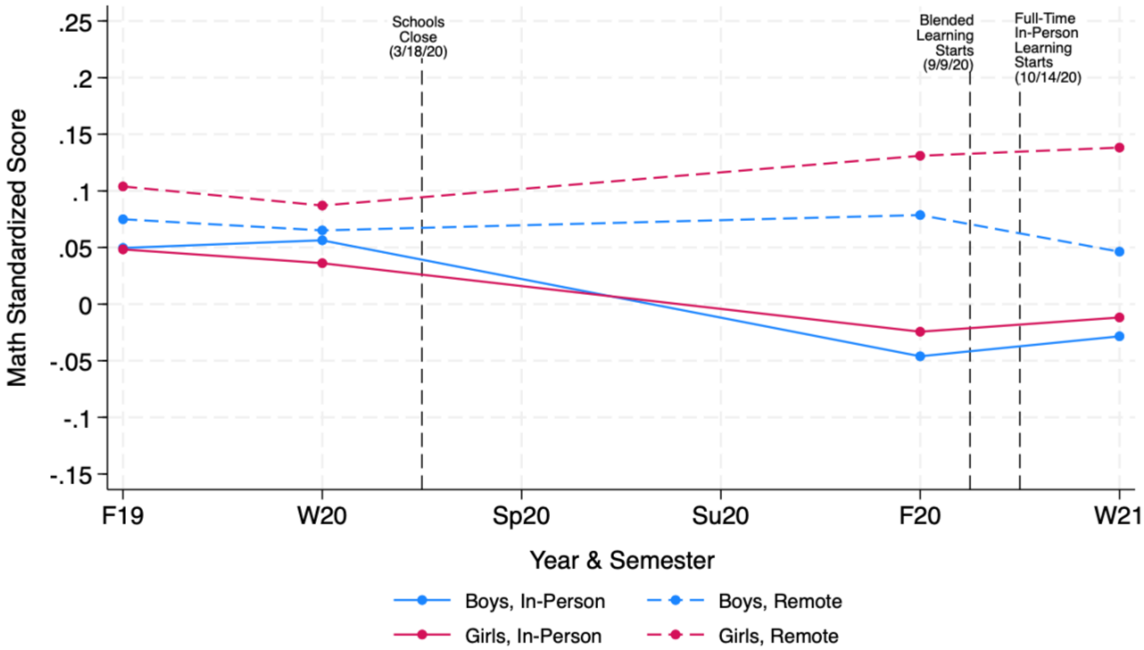


a. Math

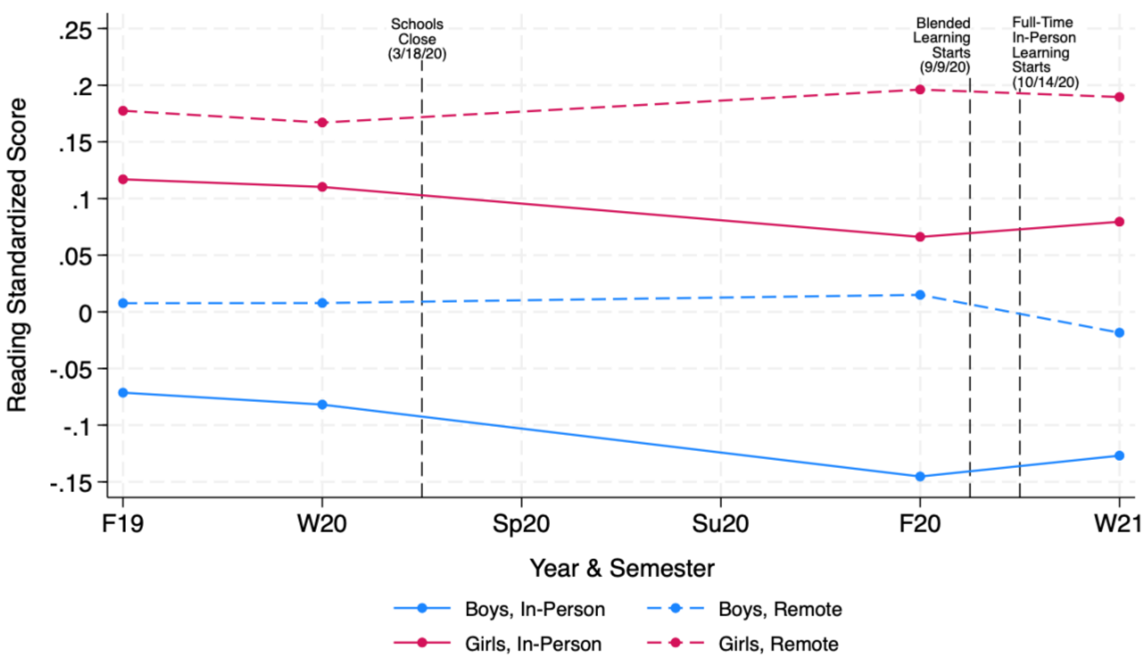


b. Reading

Figure 1.3. Standardized iReady Assessment Score Trends by Learning Mode, SY 2018-19 – SY 2020-21



a. Math



b. Reading

pandemic-induced school closures and the consequent shift in learning mode are believed to affect a range of educational inputs that are relevant for the process of skill formation of children (Werner & Woessmann, 2022). As aforesaid, the pandemic-induced remote learning likely changed the relative importance of educational inputs: student & family inputs, peer inputs, school & teacher inputs. Compared with the traditional face-to-face learning environment, students had less exposure to their peers and teachers as students and teachers were away from physical school buildings and classrooms. Effective self-regulated learning and parental support and supervision became important factors to succeed in remote learning after the initial school closure, which increased the relative importance of some student inputs X_{igst} (such as self-control and self-discipline skills) and individual/family/household time-invariant inputs ρ_i (family culture, time and resources spent on children during remote learning, for instance), whereas the transition to remote learning would have decreased the relative importance of peer inputs P_{-igst} and school/teacher inputs S_{igst}.[6] It is expected that these pandemic-engendered shifts would have resulted in a relative increase in the absolute value of the coefficient on student inputs (β_1) and a relative decrease in the absolute value of the coefficient on peer inputs and school/teacher inputs (β_2 and β_3).

1.3.2 Data

To conduct the analysis, I combine multiple administrative datasets from a metro-Atlanta school district covering the period between SY 2018-19 and SY 2020-21. The data were provided by the school district in the context of a research-practice partnership with the Metro Atlanta Policy Lab for Education (MAPLE), a component of the Georgia Policy Labs. The student-level panel dataset consists of rich information on student characteristics such as

[6] In the traditional cumulative achievement function, it is assumed that family inputs are time-invariant.

demographics, free or reduced-price meals (FRPM) status, English Learner (EL) status, types of disability, and mathematics and reading formative assessment scores. Two independent variables of interest – the proportion of historically disruptive peers and students' own self-control level – are constructed by linking the main panel dataset with Student Class and Student Discipline data; details on construction of the key variables are provided below. I restrict my sample to cohorts of students in grades 1 through 7 that (i) have attended public schools in the district (ii) have pre-pandemic records of proportion of disruptive peers and self-control level and (iii) have records of during-the-pandemic iReady assessment scores throughout the analyses period[7].

The first key variable of interest – proportion of historically disruptive peers in a classroom – is constructed by linking the Student Class and Student Discipline data. The Student Class file includes information on which classes students took in each semester of the analysis period, and Student Discipline is student-incident-level data containing information on the type and intensity of each disciplinary incident. I link the Class and Discipline datasets to identify disruptive students and determine the proportion of disruptive peers in each math and reading class.. A student is considered historically disruptive if the student committed disciplinary incidents any time from the beginning of the analysis period (fall of SY 2018-19 to the onset of the pandemic in spring SY 2019-20 and if the type of incident falls into one of the following disciplinary codes: bullying, fighting, sexual battery, sexual harassment, sex offenses, threat or intimidation, carrying weapons (knife, handgun, rifle) and other firearms, serious bodily injury, disorderly conduct, student incivility[8]. To construct the peer disruptiveness variable, I first

[7] Students in the analyses sample would be grades 2 through 8 in SY 2020-21.
[8] For detailed information on disciplinary codes and frequency of each disciplinary incidents by student in the analysis sample, refer to Appendix A2 and A3.

calculate the proportion of historically disruptive peers of all math and reading classes that each student was enrolled in:

$$prop.d_{icgst} = \frac{\sum_{p \neq i} P_{pcgst}}{n_{cgst} - 1} \quad (2)$$

where P_{pcgst} is an indicator which equals 1 if a student i's peer p in classroom c is identified as historically disruptive in pre-pandemic period, and n_{cgst} is the number of students in the classroom c. Dividing the total number of disruptive peers ($\sum_{p \neq i} P_{pcgst}$) by the class size $n_{cgst} - 1$ (excluding the student i) gives us the proportion of historically disruptive peers in each classroom c, and then I calculate the average of $prop.d_{icgst}$ for math and reading courses separately to obtain the average proportion of disruptive peers in math and reading classes for the student ($prop.d_{igst}$).

The second key variable of interest – a student's self-control level – is proxied by a "rush flag" in the main panel data.[9] Students are flagged for rushing on each of the math and reading formative assessments if that student's average time on each task of the exam were shorter than a designated time.[10] I construct the self-control variable as a dummy variable which equals 1 if students ever rushed in the exams any time in the pre-pandemic semesters.

Given that parents/guardians could choose between sending their children back to school and staying remote in fall of SY 2020-21, I employ additional data in order to conduct the analyses for the planned remote learning period, which is between fall and winter exams in SY

[9] Zamarro et al. (2020) take a similar approach, using item non-response and careless answering on surveys to serve as a proxy for grit and self-control. Among a sample of high school students, they find that both item non-response and careless answering were negatively correlated with both self-reported and teacher-reported measures of grit and self-control. Similarly, using data from a nationally representative panel of American adults, Zamarro et al. (2018) found that repeated careless answering behavior was negatively correlated with self-reported grit and self-reported conscientiousness. See also Hitt, Trivitt and Cheng (2016) and Hitt (2015), who study the relationship between survey effort and teacher reports of students' skills, academic outcomes at the end of high school, and college attendance.

[10] A student was given either a "yellow" flag or a "red" flag, indicating the student took less than 21 or 12 seconds on average to finish each task on the exams.

2020-21. The district's Blended Learning Attendance data during SY 2020-21 provide individual-level information on assigned instructional mode and whether a student attended for each instructional day.[11] I calculate the proportion of remotely attended instructional days between the fall and winter exams as follows:

$$prop.r_{igst} = \frac{cum.remote.days_{igst=W21} - cum.remote.days_{igst=F20}}{cum.attend.days_{igst=W21} - cum.attend.days_{igst=F20}} \tag{3}$$

where $cum.remote.days_{igst=W21}$ and $cum.attend.days_{igst=W21}$ are cumulative attended "remote" days and "total" cumulative attended instructional days of student i in grade g, in school s in school year t, as of the date of the winter formative assessment. Similarly, $cum.remote.days_{igst=F21}$ and $cum.attend.days_{igst=F21}$ are cumulative attended "remote" days and "total" cumulative attended instructional days as of the day of the fall formative assessment in SY 2020-21. Thus, $prop.r_{igst}$ is the proportion of remote learning days between the fall and winter formative assessments of SY 2020-21, which is calculated by dividing the number of remote attendance days between assessments by the total attendance days between assessments. For instance, if $prop.r_{igst}$ is 0.6, 60 percent of total attended instructional days between the fall and winter exams of SY 2020-21 were remote. Lastly, I use the district's Parental Survey data – which contains information on parents' preferences toward instructional modes and types of transportation to/from school in SY 2020-21 – and the number of COVID-19 positive and quarantined cases by school to instrument the proportion of remote learning days, to overcome selection bias issue raised by parental choice on learning mode.

[11] Out of five partner school districts of MAPLE, only the school district I study in this paper had detailed Blended Learning data during SY 2020-21 available. Given that detailed information on how many instructional days a student spent on each learning mode is imperative for conducting "planned blended learning" phase analysis, only students from this district are included in the analyses sample.

Tables 1.4 and 1.5 present descriptive statistics for students in the analyses sample. Table 1.4 shows the statistics for full sample (columns 1-2) and by gender (columns 3-6). 43 percent of the students in the analyses sample are Black, 25 percent are White, 10 percent are Asian, and 18 percent are Hispanic. 45 percent of the students of the sample were eligible for free or reduced-price meals, FRPM, 11 percent were students with disabilities, including seven percent of girls and 15 percent of boys. In the "Peer Composition and Self-Control" panel, I provide mean statistics of variables related to students' own disruptiveness, peers' disruptiveness, and self-control. Six percent of the students in the sample committed one or more designated disciplinary incidents during the pre-pandemic semesters (and were thus considered "historically disruptive"). Students' own disruptiveness level varied widely by gender; three percent of girls and nine percent of boys were identified as disruptive students. The mean proportion of historically disruptive peers in classrooms is seven percent for both math and reading courses. On average, 16 percent of students were an "ever-rusher" on math exams during the pre-pandemic semesters, and nine percent were an ever-rusher on pre-pandemic reading exams. Boys were 1.7 times more likely to rush on math exams and twice more likely to rush on reading exams than girls at any point during the pre-pandemic periods. The mean statistics of our outcome variables of interest, math and reading formative assessment scores, are reported in the "Achievement Scores" panel. Girls outperform boys both on math and reading exams, where the achievement gaps are much wider in reading than in math.

To check whether changes in student test taker composition may be affecting my results, I break down the analysis sample into three periods: the pre-pandemic period (fall-to-winter semesters of SY 2018-19 and 2019-20), an unplanned remote learning period (between the initial school closure and the remainder of spring SY 2019-20), and a planned remote learning period (fall SY 2020-21) and compare mean characteristics across the phases. The summary statistics are reported in Table 1.5. Between the fall and winter exams in SY 2020-21, students spent an average of 57 percent of attended instructional days in math remotely and 58 percent of attended instructional days in reading learning remotely. Considerable variation in the extent of exposure to remote instruction is evident from the magnitude of the standard deviation and can also be observed in Figure 1.4. For both math and reading, the proportion of days attended in remote learning mode was highest in the 95-100% category and second highest in the 25-30% category, reflecting the fact that universal remote learning early in the semester forced most students to spend at least 20% of the instructional days between exams in remote instruction. Few changes are observed in the demographic composition of the student sample across the phases, whereas slight shifts occurred in students' exposure to historically disruptive peers and proxied self-control level during the unplanned remote learning period. These factors return to their pre-pandemic levels during the planned remote learning.

1.3.3 Empirical Models

The analyses in the study are twofold. First, as aforementioned, I conduct an exploratory analysis to investigate the pre-pandemic relationship between being in a classroom with historically disruptive peers and academic achievement and examine whether classroom disruption was particularly problematic for girls prior to the pandemic. An analogous analysis is conducted with respect to student self-control level. Second, I investigate whether planned remote learning in the fall semester of SY 2020-21 led to changes in gender-based achievement gaps. To distinguish between the effect of disruptive peers and self-control mechanisms, I allow for differential impacts based on the classroom peers' history of disruptiveness and prior

Table 1.4. Summary Statistics – Pre-Pandemic Full Sample, by Gender

	Full Sample		Girls		Boys		Mean Differences
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	(G-B)
Demographics							
Black	0.44	0.50	0.44	0.50	0.44	0.50	0.01
White	0.25	0.43	0.25	0.43	0.25	0.44	-0.01
Asian	0.10	0.30	0.10	0.30	0.10	0.30	0.00
Hispanic	0.17	0.38	0.17	0.38	0.18	0.38	-0.01
FRPM	0.45	0.50	0.45	0.50	0.45	0.50	-0.01*
Any Disability	0.11	0.31	0.07	0.26	0.15	0.35	-0.07***
EL	0.10	0.30	0.09	0.28	0.11	0.31	-0.02***
Peer Composition and Self-Control							
Any Disruptive Behaviors	0.06	0.24	0.03	0.17	0.09	0.29	-0.06***
Proportion of Disruptive Peers (Math)	0.07	0.10	0.07	0.10	0.07	0.11	-0.00***
Proportion of Disruptive Peers (Reading)	0.07	0.11	0.07	0.10	0.07	0.11	-0.00***
Ever Rushed (Math)	0.18	0.38	0.13	0.34	0.23	0.42	-0.09***
Ever Rushed (Reading)	0.13	0.34	0.09	0.29	0.17	0.38	-0.08***
Achievement Scores							
iReady Math Scale Score	453.64	46.72	454.19	45.53	453.11	47.84	1.08***
iReady Reading Scale Score	542.90	71.67	548.99	69.09	537.04	73.59	11.96***
Growth per day (math)	0.17	0.24	0.17	0.22	0.18	0.25	-0.01***
Growth per day (reading)	0.23	0.40	0.23	0.37	0.24	0.42	-0.01**
Observations	53,388		26,375		27,013		
(Number of Students)	(36,091)		(17,817)		(18,280)		

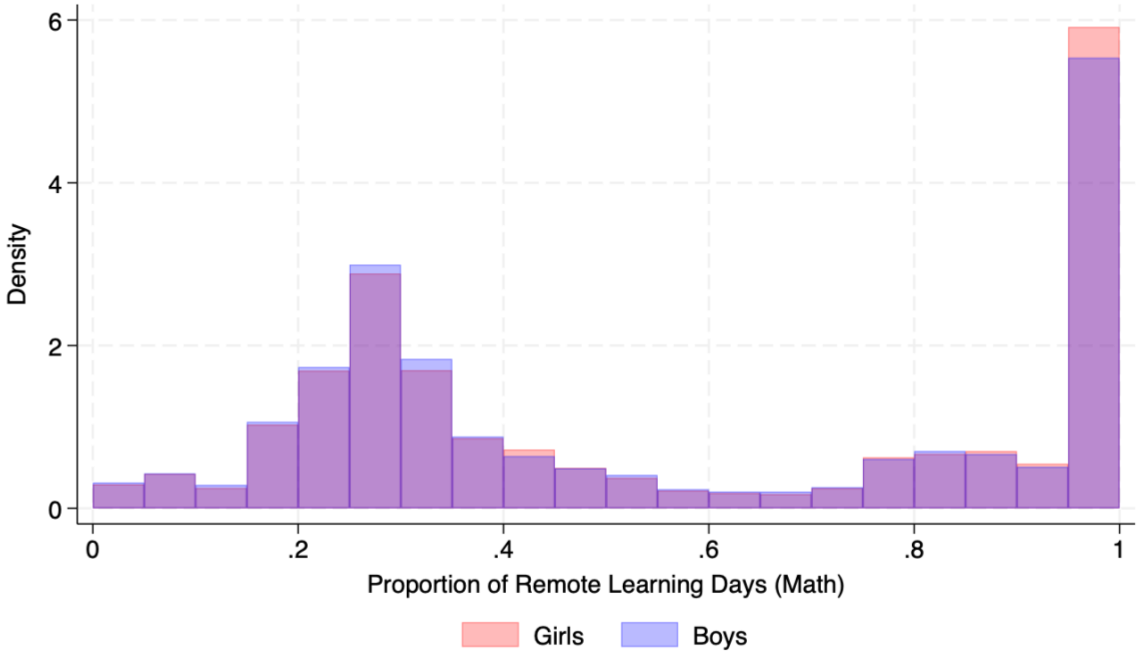
Notes: Sample includes students Grade 1 to Grade 7 enrolled in public schools located in the school district between fall to winter of SY 2018-19 - SY 2019-20. Detailed information on how students were identified as disruptive students can be found on Appendix A2. Details on Proportion of Disruptive Peers and Ever Rushed variables construction can be found in Section 1.3.2. The unit of the number of observations is individual in each school-year-semester, unique number of students are also reported in the last row.

Table 1.5. Summary Statistics – Full Sample, by Year-Semester

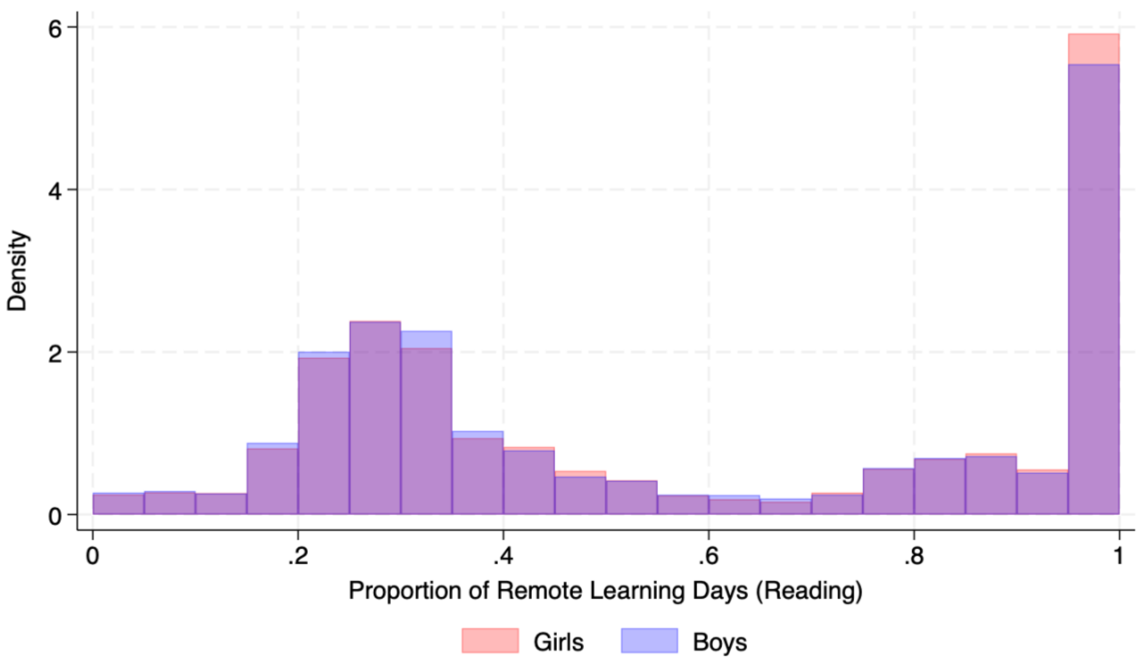
	Pre-Pandemic		Unplanned		Planned	
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Demographics						
Black	0.44	0.50	0.41	0.49	0.38	0.49
White	0.25	0.43	0.26	0.44	0.28	0.45
Asian	0.10	0.30	0.11	0.32	0.14	0.34
Hispanic	0.17	0.38	0.18	0.39	0.17	0.37
FRPM	0.45	0.50	0.49	0.50	0.44	0.50
Any Disability	0.11	0.31	0.12	0.32	0.11	0.32
EL	0.10	0.30	0.09	0.29	0.09	0.28
Learning Mode between Fall and Winter of SY 2020-21						
Remote Days Proportion (Math)					0.56	0.34
Remote Days Proportion (Reading)					0.57	0.33
Peer Composition and Self-Control Prior to the Pandemic						
Any Disruptive Behaviors	0.06	0.24	0.07	0.26	0.07	0.25
Proportion of Disruptive Peers (Math)	0.07	0.10	0.08	0.11	0.07	0.12
Proportion of Disruptive Peers (Reading)	0.07	0.11	0.08	0.11	0.06	0.11
Ever Rushed (Math)	0.18	0.38	0.18	0.38	0.17	0.38
Ever Rushed (Reading)	0.13	0.34	0.11	0.31	0.10	0.30
Achievement Scores						
iReady Math Scale Score	453.64	46.72	455.20	44.01	465.21	47.57
iReady Reading Scale Score	542.90	71.67	540.72	70.46	551.12	71.91
Growth per day (math)	0.17	0.24	-0.08	0.30	0.11	0.35
Growth per day (reading)	0.23	0.40	-0.17	0.49	0.13	0.57
Observations	53,388		27,481		21,937	

Notes: Sample includes students Grade 1 to Grade 8 enrolled in public schools located in the school district between fall to winter of SY 2018-19 – SY 2020-21. Remote Days Proportion of Math and Reading report mean statistics of attended remote learning days between fall and winter formative assessments of SY 2020-21. Detailed information on how students were identified as disruptive students can be found on Appendix A2. Details on Proportion of Disruptive Peers and Ever Rushed variables construction can be found in Section 1.3.2. The unit of the number of observations is individual in each school-year-semester.

Figure 1.4. Distribution of Exposure to Remote Instruction by Gender



a. Math



measures of students' proclivity to rush. First, I estimate the following equation over the testing period prior to the pandemic outbreak, fall-to-winter of SY 2018-19 and fall-to-winter of SY 2019-20 to explore the pre-pandemic relationship between the two mechanisms of interest and student achievement. I assume θ=1 in equation (1.2) and estimate the average change in test scores per instructional day between the fall and winter exams:

$$(\Delta y_{igst}/days_{igst}) = \beta_0 + \beta_1 female_i + \beta_2 prop.d_{igst} + \beta_3 ever.rush_{igst} + \boldsymbol{\beta_4 X_{igst}} + \lambda_g + \sigma_s + \tau_t + \epsilon_{igst} \tag{4}$$

Where Δy_{igst} is the difference in math and reading formative assessment scores between the winter and fall assessments for student i in grade g, in school s in a year-semester t. $days_{igst}$ are the number of instructional days for the student between the fall and winter exams, $female_i$ is an indicator for female students, $prop.d_{igst}$ is the proportion of historically disruptive peers in the student's fall-semester math or reading class, $ever.rush_{igst}$ is an indicator that identifies students that ever rushed in any previous pre-pandemic semesters during the sample periods[12]. In other words, $ever.rush_{igst}$ measures the student's history of proclivity to rush during the exams; it is 1 if the student ever rushed in formative assessments in any time during all previous semesters in the analyses period or 0 otherwise. $\boldsymbol{X_{igst}}$ is a vector of time-varying individual characteristics, such as the FRPM eligibility, EL status, disability status, and other relevant factors. Finally, λ_g, σ_s and τ_t refer to grade, school, and year-semester fixed effects respectively.

[12] As for $prop.d_{igst}$, I look at the history of disruptiveness of peers in a classroom in year-semester $t-1$ because the standardized tests are administered in the beginning of each semester. For example, if a dependent variable is the standardized test score in the beginning of winter of SY 2019-20, $prop.d_{igst}$ is calculated using the history of disruptiveness of fall of SY 2019-20 classroom peers.

To investigate the role of unplanned and planned remote learning in changing gender achievement gaps through the two potential mechanisms, I employ the Blinder-Oaxaca decomposition method, which was first introduced in the economics literature by Ronald Oaxaca and Alan Blinder to assess the sources of male-female wage differentials (Oaxaca, 1973; Blinder, 1973; Jann, 2008). I decompose differences in formative assessment scores between girls and boys into three parts that could potentially explain the mean differences: (i) group mean differences in characteristics, (ii) group differences in the marginal effects of characteristics on test scores (including differences in the intercept), and (iii) an interaction term accounting for the fact that differences in the first and second components exist simultaneously between girls and boys. The difference in average formative assessment growth per day between girls (G) and boys (B) due to constant unmeasured factors, peer influences, and lack of self-control can be decomposed as follows:

$$(\overline{\Delta y_{igst}/days_{igst}}) = (\overline{\Delta y_{igst}/days^{G}_{igst}}) - (\overline{\Delta y_{igst}/days^{B}_{igst}})$$

$$= (\beta^G_0 - \beta^B_0) + \left[\beta^B_1\left(\Delta\overline{prop.d_t}\right) + (\beta^G_1 - \beta^B_1)\left(\overline{prop.d^B_t}\right) + (\beta^G_1 - \beta^B_1)\left(\Delta\overline{prop.d_t}\right)\right]$$

$$+ \left[\beta^B_2\left(\Delta\overline{ever.rush_t}\right) + (\beta^G_2 - \beta^B_2)\left(\overline{ever.rush^B_t}\right) + (\beta^G_2 - \beta^B_2)\left(\Delta\overline{ever.rush_t}\right)\right] \quad (5)$$

where $\Delta\overline{prop.d_t}$ is the difference between girls and boys in mean proportions of disruptive classroom peers, i.e. $\overline{prop.d^G_t} - \overline{prop.d^B_t}$, and $\Delta\overline{ever.rush_t}$ is the difference in the mean proportions of past rushing between girls and boys ($\overline{ever.rush^G_t} - \overline{ever.rush^B_t}$). $(\beta^G_0 - \beta^B_0)$ represents the time-constant difference in outcomes for girls and boys that is due to unobserved gender differences not measured by explanatory variables in equation (4). β^B_1 is the marginal effect of disruptive peers on boys, and $(\beta^G_1 - \beta^B_1)$ is the difference in the marginal effect of disruptive peers between girls and boys. β^B_2 and $(\beta^G_2 - \beta^B_2)$ represent the same components of the rush indicator. The first bracketed term is the difference in outcomes between girls and boys that is due to the influences of disruptive peers. It has three components: differences due to differences in exposure to disruptive peers ($\beta_1^B\left(\Delta\overline{prop.d_t}\right)$), differences due to differences in the marginal effect of disruptive peers ($(\beta_1^G - \beta_1^B)\left(\overline{prop.d_t^B}\right)$), and the interaction of differences in the marginal effect and differences in exposure ($(\beta_1^G - \beta_1^B)\left(\Delta\overline{prop.d_t}\right)$). The second bracketed term represents the difference in outcomes due to lack of self-control, with components analogous to those for peer influences.

To understand how unplanned and planned remote instruction affected gender differences in outcomes, I first estimate the achievement growth model (equation (4)) over the period from the winter (December/January) of SY 2019-20 to fall of SY 2020-21, which encompasses roughly 10-weeks of pre-pandemic in-person instruction, 9-weeks of unplanned remote learning from mid-March to the end of May, and summer vacation in June and July. Second, I estimate the model for the planned remote period between the fall and winter exams in SY 2020-21. I concentrate on how the bracketed terms in equation (5) change, relative to the pre-pandemic period.

For the unplanned remote instruction period, the class peer composition should not have changed significantly from prior periods given the switch to remote learning was unplanned and there was no parental choice over learning mode. Likewise, the past proclivity of boys and girls to rush through exams should not have changed. Further, the interaction component in the first bracketed term, which is the product of two changes, should be small. Consequently, the key items of interest are changes to the marginal effects of disruptive peers on boys and girls (β_1^B and β_1^G), and changes to the marginal effects of lack of self-control on boys and girls (β_2^B and β_2^G). If remote learning dampens peer influences, one would expect either the absolute value of β_1^B to decrease or the effect fade away, though the change in the difference in marginal effects between girls and boys ($\beta_1^G - \beta_1^B$), is unclear, a priori. If remote learning requires greater self-control, then the absolute value of the marginal effects of prior "rushing" should increase. Even if the difference in marginal effects ($\beta_2^G - \beta_2^B$) does not change, the gender difference in outcomes would change if β_2^B changes from the pre-pandemic period to the unplanned-remote-learning period (the term $\beta_2^B\left(\Delta\overline{ever.rush_t}\right)$ in the equation (5) would increase). Thus, if girls have greater self-control on average than to do boys ($\Delta\overline{ever.rush_t}$ < 0), then the unplanned shift to remote learning would increase gender achievement gaps assuming prior rushing has a negative effect on test scores for both boys and girls.

As discussed above, several metro-Atlanta school districts began to offer in-person instruction at varying times during SY 2020-21, while maintaining remote learning as an option. Given that parents could choose the learning mode option for their child, this likely lead to changes in the peer composition of both in-person and remote classrooms. The marginal effects of peer composition and own self-control would also vary with learning model choice. To measure these changes and their corresponding impact of gender achievement growth differentials, I conduct the decomposition for the planned remote learning period (between the fall and winter exams in SY 2020-21), additionally controlling for the interaction terms of the proportion of remote learning and two key mechanisms (proportion of disruptive peers and self-control level).

Given that the analyses period of the unplanned, emergent remote learning include summer of SY 2019-20, the estimates might pick up the impacts of the nine-week unplanned remote learning as well as the following summer. Henceforth, I focus on documenting results for the pre-pandemic and planned remote learning periods in the next section.

1.4 Results

1.4.1 Pre-Pandemic Relationship between Disruptive Peers, Self-Control, and Student Achievement

Before diving into the main analyses results, I first report estimates of the pre-pandemic relationship between the two mechanisms of interest and student achievement as well as the gender disparities in math and reading achievement scores prior to the onset of the pandemic. Table 1.6 shows ordinary least squares (OLS) estimates of the achievement-growth-per-day model for the full sample and by gender, where I report the pre-pandemic relationship between students' achievement (in terms of standardized mathematics and reading formative assessment scores) and 1) proportion of historically disruptive peers in classroom and 2) students' past proclivity to rush. Each column displays the estimated coefficients and robust standard errors (in parentheses) of each model specification. Model (1) only controls for the female indicator, Model (2) includes two independent variables of interest, Model (3) includes all other controls such as student demographics and characteristics, household's socioeconomic status measured by FRPM eligibility, and prior achievement. Lastly, Model (4) controls for grade, school, and year-semester fixed effects as well as all other variables that were previously included in previous identification. The estimated coefficients on the proportion of disruptive peers and the ever-rushed indicator confirm prevalent beliefs that classroom disruptiveness and lack of self-control have negative impacts on student achievement on average. In Model (4), which is my preferred specification, I find that a 10 percentage point increase in the proportion of historically disruptive peers in classrooms decrease math (reading) formative assessment scores by 0.03 (0.02) standard deviations and being an "ever-rusher" decreases the math (reading) scores by

0.05 (0.07) standard deviations. Female students outperform boys in reading but underperform them in math.

1.4.2 Planned Remote Learning

Next, I present results for the Blinder-Oaxaca decomposition for math and reading in Tables 1.7. The decomposition attributes the difference in mean outcomes between boys and girls to each set of controls: proportion of disruptive peers, self-control, previous achievement, proportion of remote learning (between fall and winter of SY 2020-21), and other relevant factors. The top three rows in both tables show total math (reading) gender achievement gap, the gender gaps due to (i) mean differences, ii) differences in marginal impact, and (iii) interaction between the two components. The next two panels report detailed decomposition results and share of the total gender gaps explained by gender-based difference in mean and impact (coefficient) of each control in the model. Each set of column shows the decomposition estimates for the math and reading respectively. First, note that there are two types of signs on each component. If positive, the component "widens" the gender achievement gap between girls and boys, and "closes" the gender achievement gap if negative. On math exams, the (per day) gender achievement growth gap between girls and boys is about -0.01 scale score points during the pre-pandemic semesters where 2 and 94 percent of the gender gap can be explained by the differences in the mean and differing impacts between girls and boys, respectively[13]. This implies that before the pandemic-induced school closure, the gap favored boys by 0.01 scale score points.

The transition to the planned remote learning resulted in widened gender achievement growth gaps in both math and reading; now the total gaps are about 0.01 scale score points that

[13] This is not reported on the main analyses table (Table 1.7); Table 1.7 only reports the main decomposition results for math and reading of the planned remote learning analyses.

favor girls in both subjects. Given that a school year typically has 180 instructional days (or 90 instructional days per semester), the gap corresponds to about 2 to 3 scale score points per academic year. Focusing on the factors that widen the gender achievement growth gap between girls and boys (ones with a positive sign), the total gender gap in math is mainly attributed to the mean difference in the disability status and impact difference in i) the proportion of remote learning and ii) and the interaction term “Proportion of Remote Learning × Proportion of Disruptive Peers”. Particularly, differing mean of percentage of girls and boys with disability explains about 12 percent of the total gender gap in math. Moreover, differing impact of the proportion of remote learning and the interaction term of the proportion of remote learning and the proportion of disruptive peers explain significant amount of the total gap. This implies that the exposure to remote learning and disruptive peers in classroom had differential impact on girls and boys which resulted in widening gender achievement gap between girls and boys, favoring girls. This is consistent to one of my hypotheses, that the differential impact of remote learning and disruptive peers would favor girl. Meanwhile, differing mean of “Proportion of Remote Learning × Ever Rushed” does not explain statistically significant share of the gap, which is contrary to my other hypotheses that differing mean of self-control level between girls and boys would explain the widened gender achievement gap. Lastly, differing impact of grade dummies between girls and boys also explains considerable amount of the total achievement gap. One potential explanation to this result is that girls get more academically matured than boys in the same age.

Similar patterns are detected in reading results, except that differing impact of the interaction term, “Proportion of Remote Learning × Proportion of Disruptive Peers, no longer widens the total gap as well as explain considerable share of the total gap in reading. Grade

Table 1.6. Pre-Pandemic Relationship (OLS Results) by Subject

	(1)		(2)		(3)		(4)	
	Math	Reading	Math	Reading	Math	Reading	Math	Reading
Female	0.024***	0.196***	-0.051***	0.132***	-0.035***	0.013***	-0.036***	0.012***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.004)	(0.004)	(0.004)	(0.004)
Proportion of Disruptive Peers			-2.739***	-2.491***	-0.164***	-0.106***	-0.280***	-0.232***
			(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)
Ever Rushed			-0.734***	-0.774***	-0.062***	-0.068***	-0.050***	-0.066***
			(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Previous Achievement					0.795***	0.789***	0.792***	0.782***
					(0.003)	(0.003)	(0.003)	(0.003)
Black (ref. White)					-0.121***	-0.106***	-0.094***	-0.076***
					(0.01)	(0.01)	(0.01)	(0.01)
Asian					0.062***	0.027***	0.047***	0.011***
					(0.01)	(0.01)	(0.01)	(0.01)
Hispanic					-0.060***	-0.064***	-0.052***	-0.052***
					(0.01)	(0.01)	(0.01)	(0.01)
FRPM					-0.065***	-0.061***	-0.057***	-0.045***
					(0.01)	(0.01)	(0.01)	(0.01)
Disability					-0.181***	-0.173***	-0.184***	-0.174***
					(0.01)	(0.01)	(0.01)	(0.01)
EL					-0.098***	-0.132***	-0.080***	-0.125***
					(0.01)	(0.01)	(0.01)	(0.01)
Controls					Y	Y	Y	Y
Grade FE							Y	Y
School FE							Y	Y
Year-Semester FE							Y	Y
Observations	53,390	53,361	53,388	52,250	53,388	50,370	53,388	50,370

Notes: Analyses Sample includes students Grade 1 to Grade 7 enrolled in public schools located in the school district during the pre-pandemic semesters (between fall to winter of SY 2018-19 - SY 2019-20). Robust standard error in parentheses. The unit of the number of observations is individual in each school-year-semester, so if a student was observed during the entire pre-pandemic period, there would be two observations for each student. Outcome variables achievement-growth-per-day of math and reading achievement scores. * p<0.1 ** p<0.05 *** p<0.01.

Table 1.7. Detailed Blinder-Oaxaca Decomposition Results, Math and Reading

	Planned Remote			
	Math		Reading	
	Amount	%	Amount	%
Total Gender Gap ($\bar{y}_t^G - \bar{y}_t^B$)	0.0106**	100%	0.0139**	100%
Endowments	0.0002	2%	-0.0028	-20%
Coefficients	0.0066	62%	0.0105	76%
Interaction	0.0038**	36%	0.0062**	45%
Differing Mean of:				
Proportion of Disruptive Peers	-0.000001	<1%	-0.0002	-1%
Ever Rushed	-0.000006	<1%	-0.0023	-17%
Proportion of Remote Learning	-0.0007**	-7%	-0.0013***	-9%
Proportion of Remote Learning × Proportion of Disruptive Peers	-0.00004	<1%	-0.0001	<1%
Proportion of Remote Learning × Ever Rushed	0.0001	1%	0.0009	6%
Number of Incidents	0.0002	2%	-0.00001	<1%
Race	-0.0002	-2%	-0.00004	<1%
FRPM	0.00004	<1%	-0.0002	-1%
EL	0.0001	1%	-0.0007**	-5%
Disability	0.0013*	12%	0.0016	12%
Grade FE	-0.0004	-8%	-0.0005	-4%
Differing Impact of:				
Proportion of Disruptive Peers	-0.0061	-58%	0.0039	28%
Ever Rushed	0.0051	48%	-0.0064	-46%
Proportion of Remote Learning	0.0211**	199%	0.0375***	270%
Proportion of Remote Learning × Proportion of Disruptive Peers	0.0104*	98%	-0.0105	-76%
Proportion of Remote Learning × Ever Rushed	-0.0068	-64%	0.0028	20%
Number of Incidents	-0.0004	-8%	-0.0002	-1%
Race	0.0012	11%	0.0114	82%
FRPM	0.0022	21%	-0.0022	-16%
EL	0.0002	2%	-0.0023	-17%
Disability	-0.0028	-26%	-0.0048	-35%
Grade FE	0.0337**	318%	0.0028	20%
Constant ($\beta_0^G - \beta_0^B$)	-0.0515***	-486%	-0.0216	-155%
Observations	25,547		29,340	

Notes: Analyses sample includes students in Grade 2 through Grade 8 enrolled in public schools located in the school district over the period of SY 2018-19 - SY 2020-21. The unit of the number of observations is individual in each school-year-semester. Pre-pandemic period includes 2 semesters (fall to winter of SY 2018-19 and SY 2019-20) prior to the school closure and planned remote learning period includes fall-to-winter of SY 2020-21.
* p<0.1 ** p<0.05 *** p<0.01.

dummies also do not explain statistically significant share of the total gap. Differing impact of the proportion of remote learning between girls and boys explains larger share of the total reading gap, comparing to math.

1.5 Conclusion

The COVID-19 pandemic and related school closures undoubtedly affected many aspects of people's lives. Especially for students, the pandemic-induced shift to remote learning has unprecedentedly altered the nature of their learning environment: being away from school buildings, peers, and teachers, and learning from home under parents' and guardians' supervision. Since the initial onset of the COVID-19 pandemic, remote learning has received great attention and the importance of self-regulated learning has been stressed ever than before (Berger et al., 2021). In fact, remote learning is now commonly offered as an alternative to the traditional in-person learning; nearly all of the United States' largest school districts announced to continue providing a remote option as well as expanding their virtual learning offerings for the fall of SY 2022-2023, and several states intermittently switched to remote learning or dismiss students early in the day when cities within the states experience hot days at schools (Belsha and Barnum, 2022; Will, 2022).

In this paper, I study the impact of the pandemic-induced remote learning on student achievement and gender achievement gaps, focusing on the change in relative importance of impacts from disruptive peers and students' own self-control level due to the pandemic. I find that gender achievement growth gaps in both math and reading widen throughout the series of pandemic-induced shifts to remote learning. Findings on disproportionate impact of the pandemic-induced remote learning by gender and subsequent gender achievement gap raise concerns since such exacerbated gaps could translate into larger gaps in future outcomes, such as post-secondary school outcomes and earnings. Moreover, additional findings on the negative consequences of remote learning versus in-person learning due to the pandemic outbreak on top of the findings from previous literature are also worrisome, given there has been growing supply and demand of distance learning as discussed earlier (Jack et al., 2022; Tagami, 2022). Based on the results that the gender-based impact differences in remote learning and disruptive peers in classroom contribute to the widened achievement gaps between girls and boys, it is suggested to identify and support students struggling in different learning modes and continue monitoring students' disciplinary behaviors given that districts are experiencing a surge in student disciplinary incidents, seemingly induced by the pandemic, along with the existing research showing clear evidence of negative impacts of disruptive peers in classrooms (Hoxby, 2000; Carrell et al., 2018; Wile, 2022; Downey, 2022; McCray, 2022). Also, while contribution is statistically insignificant, higher self-control resulted in better academic performance during the pre-pandemic period. Since there is a possibility that the proxy I used for student's self-control level does not accurately estimate their self-control level, another potential way to support girls and boys over the course of the pandemic-induced shift in learning environment would be to consider devising an alternative measurement of students' non-cognitive skills that are essential to successfully navigate through self-regulated learning, such as self-control and perseverance, and accordingly support students in need. School districts could offer several remedies to students participating or have participated in various learning modes and provide additional supports to students lacking self-control and self-discipline to catch upon the learning disruption caused by the pandemic.

One key threat to the study is that I do not observe any variables related to parents and household characteristics. While some children had affluent resources from their parents, others did not necessarily have such support at home. Moreover, it is believed that parents allocate more efforts to girls than to boys, and there is a negative correlation between parental efforts and prior achievement (Bonesrønning, 2010) Unfortunately, the analyses with respect to family inputs are beyond the scope of this paper since I cannot control for any family-related variables in the analysis reported in this paper. Nevertheless, the analyses provide the overall snapshot of what has happened over the course of the pandemic, and the results would provide valuable information to the districts, policymakers, and parents for making future decisions. While my primary focus in this paper lies in decomposing the gender achievement gaps and examining the average effects of remote learning induced by the pandemic among a pooled sample of students from grades 1 to 8, it is imperative to conduct further analysis to comprehensively investigate the underlying mechanisms contributing to these gender disparities. Specifically, it is crucial to explore which specific subgroups of students within the same gender were disproportionately affected by remote learning and subsequently experienced more substantial achievement disparities.

Chapter 2: The Effect of Universal Gaming Shutdown Policy in South Korea

2.1 Introduction

In 2018, the World Health Organization (WHO) made the decision to include "gaming disorder" as a clinically recognizable and significant syndrome in the 11th edition of the International Classification of Diseases (ICD-11). This disorder is defined as a pattern of gaming behavior characterized by impaired control over gaming and an increasing priority given to gaming over other activities. The inclusion of gaming disorder in the ICD-11 mandates that Member States of the WHO consider this disorder when planning and making decisions regarding healthcare and other relevant prevention measures to monitor trends of disorders (WHO, 2020). Recent research suggests that excessive online gaming may lead to symptoms that are commonly experienced among substance addicts, such as aggressive behaviors, salience, mood modification, craving, and lack of tolerance (Anderson & Bushman, 2001; Anderson & Dill, 2000; Ko et al., 2009; Kuss & Griffiths, 2012; Mehroof & Griffiths, 2010). In addition, a separate body of literature examining the link between excessive video game playing and academic performance reveals that there is an adverse association between the amount of time spent playing online games and academic achievement (Yılmaz et al., 2018; Anderson & Dill, 2000; Gentile et al. 2004; Harris & Williams, 1985; Sharif & Sargent, 2006). As a result, there is an increasing awareness among health professionals and experts about the risks associated with the development of gaming disorder (Kamenetz, 2019; Chung et al. 2019). The WHO's decision to include gaming disorder in the ICD-11 highlights the importance of recognizing and addressing this disorder as a public health concern.

South Korea, with its fast internet speeds and popularity of gaming among adolescents, has experienced, and continues to face, significant challenges associated with gaming disorder and addiction. According to a recent reported published by Korea Creative Content Agency (KOCCA) in 2021, 80.9 percent of teenagers played games at least once a year, and among them, 3.5 percent self-reported as being addicted to gaming. The issue of teenagers addicted to gaming and smartphones is of significant concern to the South Korean government and health officials (Sullivan, 2019). While only a small proportion of the population is affected by the gaming disorder and addiction, the negative impact on the daily lives and overall physical and psychological well-being of heavy gamers is profound (Jo et al., 2020). These individuals often exhibit highly problematic gaming behaviors, which can have devastating consequences for themselves and those around them.

In response to the growing concerns surrounding gaming disorder and its associated risks, such as sleep deprivation and poor academic performance, the South Korean government introduced a nationwide gaming “Shutdown Policy” in late 2011, implemented in the beginning of 2012. This policy mandates that children under the age of 16 are prohibited from playing online games between the hours of midnight and 6am. While the implementation and effectiveness of this policy have been a subject of controversy, policymakers hoped to address the issue of gaming addiction and prevent its negative consequences. Several studies have systematically investigated the impact of the policy on various outcomes, including sleep patterns, internet usage/addiction, and game industry as a whole (Jeon, 2014; Sung, 2014; Lee, 2015; Sang et al., 2017; Lee et al., 2017; Choi et al., 2018). As a recent contribution to the existing body of the literature, Lee et al. (2017) examines the initial effects of the gaming shutdown policy on internet usage and sleep duration among young individuals. Utilizing data from the 2011 and 2012 Korea Youth Risk Behavior Survey (KYRBS), which encompasses a comprehensive range of information on middle and high school students aged 13 to 18, the authors find that the implementation of the late-night online gaming ban led to a 1.6 percentage point increase in the likelihood of belonging to a high-ranked internet usage group, a decrease of 0.7 percentage points in the probability of internet addiction, and an increase of 1.5 minutes in sleep duration. Expanding on the same dataset but over a longer timeframe, Choi et al. (2018) employed the survey data from 2011 to 2015 to estimate the impact of the shutdown policy on internet use, internet addiction, and sleep duration among Korean adolescents. Through a difference-in-differences analyses, where treatment group and control group consist of students aged 15 or below and aged 16 and above respectively, the authors estimate a decline in internet use of approximately 10 percent in the treatment group during the first year (2012) of the policy enforcement. However, subsequent years demonstrated no statistically significant impact of the policy on mean weekly internet usage, with a slight increase of about 5 minutes on mean weekend internet usage in 2015, suggesting limited effectiveness of the policy in subsequent years. Additionally, little to no significant effects were found regarding sleep duration and the proportion of internet-addicted adolescents.

While existing studies have investigated the immediate or short-term impact of the policy on average sleep duration, gaming hours, internet usage and addiction, they have primarily focused on estimating the overall treatment effect of the policy, rather than delving further into the heterogeneous impact based on individuals' prior gaming behaviors. Moreover, the introduction of the "Selective Game Hours System", which came into effect months after the initial gaming shutdown policy, may have introduced confounding effects on outcomes of interest, raising doubts on using students aged over 16 as a control group. This suggests it is premature to conclude the policy had little or no impact on students, without taking their past gaming behaviors into account. Motivated by a recent study that closely aligns with the identification strategy of this paper, I employ a difference-in-differences method and restrict the analysis sample to a six-year panel of young students to estimate the heterogeneous impact of the policy by pre-policy gaming behavior (Jo et al., 2020). While the authors explore the heterogeneous impact by splitting the users into heavy (top 20%) and light (bottom 80%) gamers based on their past game usage, their analysis time frame only spans from July 2011 to February 2012.

2.2 Universal Gaming Shutdown Policy in South Korea

The issue of gaming addiction first gained attention in the early 2000s when the Commission on Youth Protection of South Korea, along with several civic organizations, raised concerns about the negative effects of excessive gaming. In 2005, a group of politicians proposed an amendment to the Juvenile Protection Act aimed at protecting young people from violent games and related health issues by restricting their access to online games during certain times of the day.[14] Following lengthy debates among various government departments, the "Shutdown Policy," also known as the "Cinderella Law," was signed into law on April 29, 2011. It was first implemented as a pilot program on November 20, 2011, under the jurisdiction of the Ministry of Gender Equality and Family of South Korea. The policy was tested until the end of the year and officially went into effect in January 2012 (Lee, 2015). The Shutdown Policy is a compulsory law implemented nationwide that prohibits children under 16 years of age from playing online games on any platform, including Korean gaming platforms, Xbox Live, PlayStation Network, Nintendo Online, between midnight and 6am. The primary objective of the policy was twofold: to prevent young students from being exposed to excessively violent content during late-night hours, and to promote an increase in their sleep hours. Policymakers aimed for the policy to

[14] Information on the amendment was retrieved from: https://likms.assembly.go.kr/bill/billDetail.do?billId=031265

foster an environment that would enable students to establish healthier sleep patterns, leading to an improvement in their health and academic performance at school.

After a few months, the South Korean government implemented an additional gaming restriction called the “Selective Game Hours System”, which was introduced as an extension of the initial “compulsive” gaming shutdown policy. Under the authority of the Ministry of Culture, Sports, and Tourism, this legislation enabled parents to request game time restrictions for their children under the age of 18 on online gaming platforms. These restrictions allowed parents to set specific “curfew” time to block their children from playing online games. The impact and effectiveness of both the compulsive and selective shutdown policies have been the subject of ongoing debate and continued investigation. Following a prolonged discussion, the initial “compulsive” shutdown policy was officially repealed on the final day of 2021 whereas the “selective” legislation remains in force to this day.

2.3 Methodology

2.3.1 Data

The data used in this study is a panel data spanning 7 years, obtained from the Korean Children and Youth Panel Survey (KCYPS). The survey was conducted annually from 2010 to 2016 in the months of October to December by the National Youth Policy Institute (NYPI) in South Korea. The survey followed three distinct age groups (cohorts) consisting of students and their parents/caregivers[15]. The survey participants provided extensive information on a range of topics including time use, household income, place of residence, parents’ education and employment, academic performance of the students, physical and mental health, and other demographic details. In particular, the survey provides detailed data on how children spend their

[15] Students were surveyed by interview, and their parents or caregivers were surveyed by telephone. Detailed information about the survey and the data archive were retrieved from: https://www.nypi.re.kr/archive/mps

time engaging in various activities, including gaming, sleeping, tutoring, doing homework, watching tv and video, and so forth. The structure of the KCYPS 2010 survey is presented in Table 2.1. Students in three different cohorts, namely E1 (grade 1 in elementary), E4 (grade 4 in elementary), and M1 (grade 1 in middle school) cohorts were surveyed since the first wave of the KCYPS in the calendar year of 2010. A total of 7,071 students participated in the first wave of the survey, with 2,342 students in the E1 cohort, 2,378 students in the E4 cohort, and 2,351 students in the M1 cohort. The sample retention rates, or response rates, for these cohorts were 85.5 percent, 83.2 percent, and 80 percent, respectively. This corresponds to a final sample size of 2,002, 1,979, and 1,881 students for each cohort. I restrict the analysis sample to the E4 cohort as I expect minimal impact from the E1 cohort due to their young age, and the students in the M1 cohort were no longer subject to the policy after one year of its implementation.

Table 2.1. Structure of KCYPS 2010 Survey

	Wave 1 (2010)	Wave 2 (2011)	Wave 3 (2012)	Wave 4 (2013)	Wave 5 (2014)	Wave 6 (2015)	Wave 7 (2016)
E1 cohort	E1(7)						
		E2(8)					
			E3(9)				
E4 cohort	E4(10)			E4(10)			
		E5(11)			E5(11)		
			E6(12)			E6(12)	
M1 cohort	M1(13)			M1(13)			M1(13)
		M2(14)			M2(14)		
			M3(15)			M3(15)	
				H1(16)			H1(16)
					H2(17)		
						H3(18)	
							C1(19)

Source: KCYPS 2010 of National Youth Policy Institute (NYPI) of South Korea, https://www.nypi.re.kr/archive/board?menuId=MENU00220.
Notes: Students in E1, E4, M1 cohorts were initially the 1st, 4th, and 7th grades respectively in the first wave of the survey. Ages in parentheses. Wave 3 in 2012 was the first year of the policy implementation (shaded gray). Analysis sample includes students in the E4 cohort that did not drop out of school for the analysis period (2010-2016).

Table 2.2. Summary Statistics – Full Sample, by Treatment Group

	Full Sample		Treatment Group (Heavy Gamers)		Comparison Group (Light Gamers)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Characteristics						
Age	12.70	2.05	12.71	2.05	12.70	2.05
Female	0.47	0.50	0.36	0.48	0.59	0.49
Pre-Policy Gaming Hours	1.05	0.70	1.58	0.61	0.54	0.25
Dad Employed	0.98	0.14	0.97	0.16	0.99	0.11
Mom Employed	0.64	0.48	0.66	0.47	0.63	0.48
Income (USD)	36,973	20,674	33,963	17,884	39,845	22,654
Education Cost	35.44	21.17	32.92	19.43	37.61	22.33
Have Siblings	0.89	0.32	0.86	0.35	0.91	0.28
Have Religion	0.48	0.50	0.47	0.50	0.49	0.50
Time Use (hours)						
Gaming	1.26	1.11	1.63	1.19	0.91	0.90
Computer	1.36	1.04	1.69	1.13	1.03	0.81
Sleep	8.26	1.15	8.27	1.15	8.24	1.14
Tutoring	1.47	1.19	1.32	1.17	1.61	1.19
School Homework	0.63	0.56	0.60	0.55	0.65	0.57
Tutoring Homework	1.47	1.19	1.32	1.17	1.61	1.19
Reading	0.61	0.67	0.57	0.67	0.65	0.68
Watching TV/Video	1.59	1.17	1.74	1.22	1.45	1.10
Hangout with Friends	1.23	1.11	1.34	1.17	1.12	1.04
Others	0.14	0.19	0.13	0.19	0.15	0.20
Computer Game (scale of 1 to 5)	3.05	1.01	3.34	0.88	2.76	1.04
Cellphone Game (scale of 1 to 5)	2.88	1.04	3.03	1.01	2.73	1.05
Observations	16,639		8,463		8,176	

Source: KCYPS 2010-2016 of National Youth Policy Institute (NYPI) of South Korea, https://www.nypi.re.kr/archive/board?menuId=MENU00220.
Notes: Sample includes students in the E4 cohort of the KCYPS 2010. All of the time use hours were calculated by [(5*weekday hours)+(2*weekend hours)]/7. "Tutoring Hours" include after-school and private tutoring.

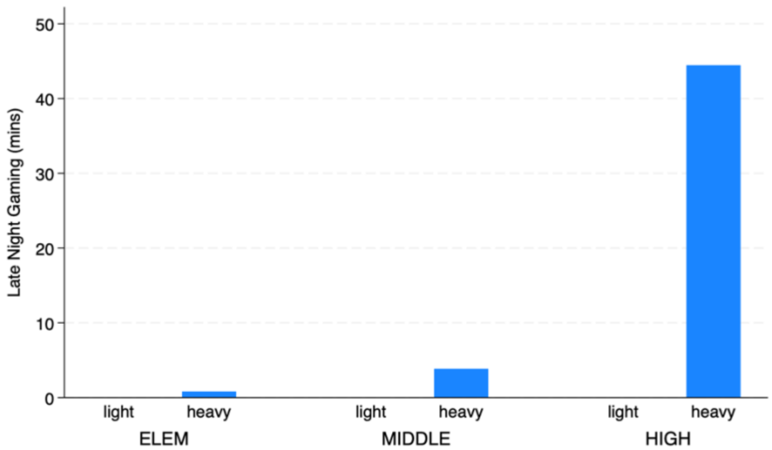
Table 2.3. Summary Statistics – by Pre-/Post-Policy and Treatment Group

	Pre-Policy				Post-Policy			
	Treatment Group		Comparison Group		Treatment Group		Comparison Group	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Characteristics								
Age	10.21	0.68	10.20	0.68	13.71	1.49	13.70	1.49
Female	0.36	0.48	0.59	0.49	0.36	0.48	0.59	0.49
Pre-Policy Gaming Hours	1.58	0.61	0.54	0.25	1.58	0.61	0.54	0.25
Dad Employed	0.97	0.17	0.99	0.10	0.98	0.15	0.99	0.11
Mom Employed	0.64	0.48	0.58	0.49	0.67	0.47	0.64	0.48
Income (USD)	32,647	19,776	37,759	24,233	34,542	16,954	40,759	21,867
Education Cost	27.54	17.07	32.02	18.43	34.28	19.76	38.94	22.97
Have Siblings	0.86	0.35	0.91	0.29	0.86	0.35	0.92	0.28
Have Religion	0.55	0.50	0.57	0.50	0.41	0.49	0.44	0.50
Time Use (hours)								
Gaming	1.58	0.85	0.54	0.37	1.65	1.31	1.07	1.02
Computer	1.71	0.99	0.81	0.65	1.68	1.20	1.14	0.86
Sleep	9.04	0.86	9.04	0.78	7.94	1.11	7.89	1.10
Tutoring	1.45	1.08	1.71	1.10	1.27	1.20	1.56	1.23
School Homework	0.74	0.52	0.74	0.53	0.54	0.55	0.61	0.58
Tutoring Homework	1.45	1.08	1.71	1.10	1.27	1.20	1.56	1.23
Reading	0.78	0.68	0.90	0.71	0.48	0.64	0.53	0.63
Watching TV/Video	1.96	1.22	1.47	1.08	1.64	1.21	1.44	1.11
Hangout with Friends	1.31	1.04	1.08	0.96	1.35	1.22	1.14	1.07
Others	0.21	0.22	0.22	0.22	0.10	0.17	0.12	0.18
Computer Game (scale of 1 to 5)	3.42	0.76	2.70	0.90	3.29	0.93	2.79	1.10
Cellphone Game (scale of 1 to 5)	2.70	1.01	2.32	0.90	3.14	0.99	2.88	1.06
Observations	2,336		2,418		5,840		6,045	

Source: KCYPS 2010-2016 of National Youth Policy Institute (NYPI) of South Korea, https://www.nypi.re.kr/archive/board?menuId=MENU00220.
Notes: Sample includes students in the E4 cohort of the KCYPS 2010. All of the time use hours were calculated by [(5*weekday hours)+(2*weekend hours)]/7. "Tutoring Hours" include after-school and private tutoring.

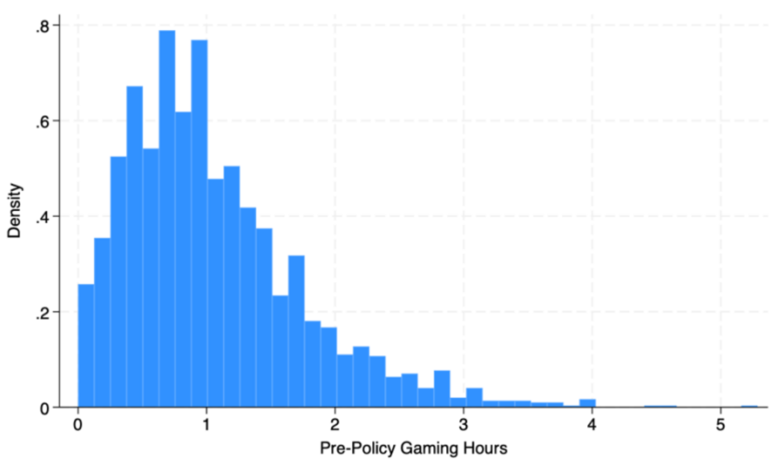
Tables 2.2 and 2.3 present the summary statistics of a set of independent variables (top panel) and dependent variables (bottom panel) of a full sample (E4 cohort) and by treatment group and pre-/post-policy years. The treatment group is comprised of students who are heavy gamers (average of pre-policy gaming hours are above median of the distribution), while the comparison group is comprised of those who are light gamers (average of pre-policy gaming hours are below median of the distribution). The reasoning behind this is that light gamers are assumed to be less or not affected by the shutdown policy, as depicted in Figure 2.1 below.

Figure 2.1. Pre-Policy Late Night Gaming by School Level and Gamer Group



Source: KISDI 2010-2011

Figure 2.2. Pre-Policy Gaming Hours Distribution (E4 Cohort)



Source: KCYPS 2010-2011

2.3.2 Empirical Model

I use the difference-in-difference method to examine how the gaming shutdown policy affected the allocation of time among students for various activities. Specifically, I estimate the regression described below to investigate the heterogeneous effects of the policy based on their past gaming behavior:

$$y_{ipt} = \beta_0 + \beta_1 heavy_{ip} + \beta_2 post_t + \beta_3 heavy_{ip} \times post_t + \boldsymbol{\beta_4 X_{ipt}} + \lambda_i + \sigma_p + \tau_t + \epsilon_{ipt} \quad (1)$$

y_{ipt} is various time use outcomes of a student i living in a province p in year t, $heavy_{ip}$ is a dummy variable which indicates whether the individual is a heavy gamer (in a treatment group) or a light gamer (in the comparison group), and $post_t$ is a dummy variable that indicates whether it is pre- or post-policy period. $\boldsymbol{X_{ipt}}$ is a vector of time-varying individual characteristics, such as household income, type of house, parents' employment status, having any siblings, and other relevant factors. λ_i, σ_p and τ_t refer to student, province, and year fixed effects, respectively. The key coefficient is β_3, which is an estimate of the treatment effect of the policy.

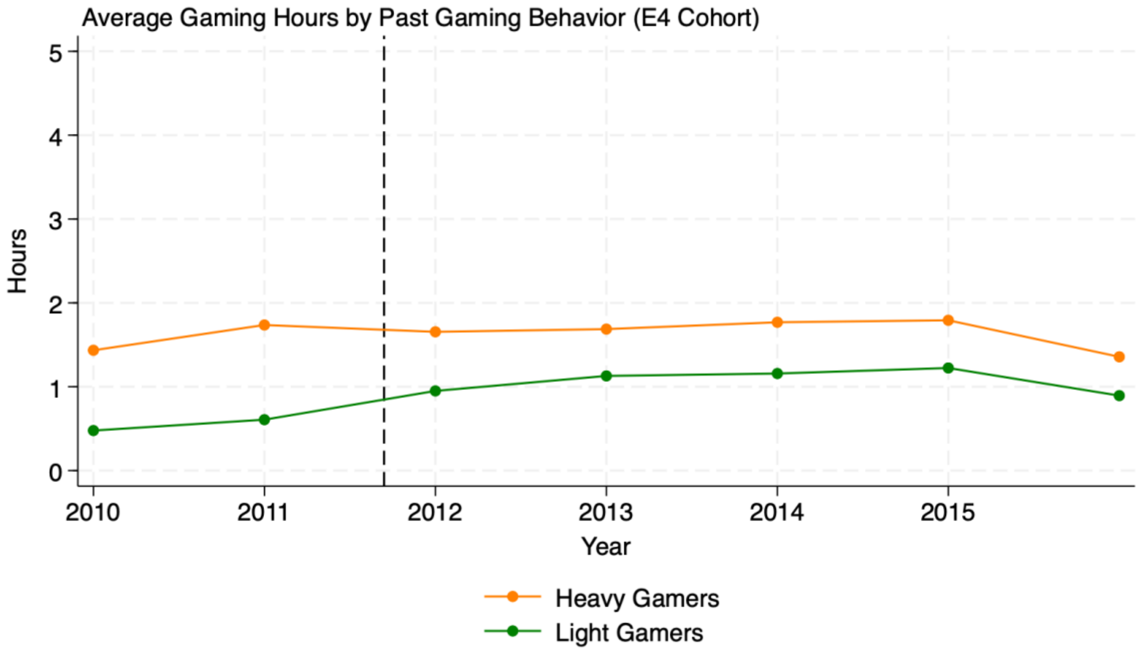
To explore variations in treatment intensity beyond binary treatment, I conduct a similar analysis, but instead of a binary treatment variable, I use a continuous treatment variable (pre_g_{ip}) as a replacement for *heavy*, as described below:

$$y_{ipt} = \beta_0 + \beta_1 pre\_g_{ip} + \beta_2 post_t + \beta_3 pre\_g_{ip} \times post_t + \boldsymbol{\beta_4 X_{ipt}} + \lambda_i + \sigma_p + \tau_t + \epsilon_{ipt} \quad (2)$$

y_{ipt} is the time use outcomes of a student i living in a province p in year t, pre_g_{ip} is a standardized pre-policy gaming hours[16]. All other notations are equivalent to the model illustrated above.

[16] A mean and a standard deviation of pre-policy gaming hours are 1.05 and 0.7, respectively.

Figure 2.3. Raw Trend of Average Gaming Hours by Treatment and Comparison Groups



Lastly, to estimate the effects of the shutdown policy over time and to examine whether there were pre-policy parallel trends across treatment and control groups, I estimate the following event study regression:

$$y_{ipt} = \beta_0 + \sum_{t=2010}^{2016} \beta_t \tau_t \times heavy_{ip} + \boldsymbol{\beta_4 X_{ipt}} + \lambda_i + \sigma_p + \tau_t + \epsilon_{ipt} \quad (2)$$

The model follows the same notation as the DID model described above. The year 2011, which is one year before the implementation of the policy, is chosen as the omitted year (year 0 in event time). The primary coefficient of interest is β_t, which allows to test the assumption of parallel trends during the pre-treatment periods as well as to measures the impact of the expansion in each post-expansion year.

2.3 Results

Tables 2.4 and 2.5 report the DID estimates of the analyses. Each column in the table represents DID models that correspond to various outcome variables (game, sleep, computer game intensity, cellphone game intensity, et cetera). For each model, the table reports the corresponding DID estimates and their robust standard errors in parentheses.

According to the DID estimate reported in the first column of Table 2.4, heavy gamers experience a decrease of approximately 25 minutes (26 percent of the base mean) in their gaming activity compared to light gamers following the implementation of the policy. Moreover, the policy resulted in a reduction in the intensity of computer gaming and cellphone gaming activities as well as in the number of hours students spend on homework, TV/video, and non-gaming computer activities. While there is a small increase in the time spent reading (by approximately 6 minutes, 7 percent of the base mean), it does not account for the entire shift in the hours on several activities. This highlights a potential limitation in the survey data. The survey does not capture all aspects of time allocation, such as physical activity, eating, and so forth, even though the time use information in the data offers some insight into the way students distribute their time among activities that are expected to be impacted by the policy implementation. This issue is discussed further in the next section.

The model with continuous treatment shows a similar pattern of results, as reported in Table 2.5. For example, a 1 standard deviation (SD) increase (0.7 hours) in pre-policy gaming hours decreases gaming hours by 0.345 hours (about 21 minutes) after the implementation of the policy. The 1 SD increase in the pre-policy gaming hours is also associated with a decrease in computer gaming and cellphone gaming intensity, hours spent on homework, watching TV/video, non-gaming computer usage and a slight increase in hours spent on reading.

Table 2.4. DID Results – Discrete Treatment

	Game	Sleep	Comp Game	Cell Game	Homework	Tutor	Tutor Homework	Read	TV/ Video	Hang	Comp
Treatment Effect	-0.411*** (0.0619)	0.0804 (0.0470)	-0.227*** (0.0479)	-0.103* (0.0521)	-0.0829*** (0.0221)	-0.0403 (0.0541)	-0.0403 (0.0541)	0.0538** (0.0220)	-0.247*** (0.0414)	-0.0811 (0.0509)	-0.351*** (0.0494)
Base mean	1.58	9.04	3.42	2.70	0.74	1.45	1.45	0.78	1.96	1.31	1.71
Observations	12,596	12,511	11,226	11,268	12,537	12,567	12,567	12,554	12,565	12,575	11,216

Notes: Sample includes students in the E4 cohort of the KCYPS 2010. All of the time use hours were calculated by [(5*weekday hours)+(2*weekend hours)]/7. Base mean is pre-policy mean of treatment group (heavy gamers). "Tutoring Hours" include after-school and private tutoring. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5. DID Results – Continuous Treatment

	Game	Sleep	Comp Game	Cell Game	Homework	Tutor	Tutor Homework	Read	TV/ Video	Hang	Comp
Treatment Effect	-0.345*** (0.0512)	0.0348 (0.0228)	-0.153*** (0.0308)	-0.0789* (0.0388)	-0.0342** (0.0143)	0.00317 (0.0287)	0.00317 (0.0287)	0.0311* (0.0176)	-0.239*** (0.0225)	-0.0451 (0.0306)	-0.282*** (0.0390)
Base mean	1.58	9.04	3.42	2.70	0.74	1.45	1.45	0.78	1.96	1.31	1.71
Observations	12,596	12,511	11,226	11,268	12,537	12,567	12,567	12,554	12,565	12,575	11,216

Notes: Sample includes students in the E4 cohort of the KCYPS 2010. All of the time use hours were calculated by [(5*weekday hours)+(2*weekend hours)]/7. Base mean is pre-policy mean of treatment group (heavy gamers). "Tutoring Hours" include after-school and private tutoring. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6. Event Study Results – Discrete Treatment

	(1) Game	(2) TV/Video	(3) Compgame	(4) Cellgame
y2010=1 # treat1=1	-0.131*	0.125**	0.0524	0.0595
	(0.0628)	(0.0579)	(0.0302)	(0.0601)
y2011=0	0	0	0	0
y2012=1 # treat1=1	-0.386***	-0.0626	-0.162***	-0.157*
	(0.0635)	(0.0798)	(0.0416)	(0.0881)
y2013=1 # treat1=1	-0.497***	-0.127**	-0.152**	-0.0798
	(0.0725)	(0.0512)	(0.0622)	(0.107)
y2014=1 # treat1=1	-0.400**	-0.248***	-0.292***	-0.102
	(0.139)	(0.0609)	(0.0539)	(0.0826)
y2015=1 # treat1=1	-0.466***	-0.237**	-0.248***	-0.0852
	(0.111)	(0.0901)	(0.0574)	(0.0687)
y2016=1 # treat1=1	-0.641***	-0.292***	-0.177	0.0560
	(0.0747)	(0.0972)	(0.109)	(0.0624)
Observations	12596	12565	11226	11268

Notes: Sample includes students in the E4 cohort of the KCYPS 2010. All of the time use hours were calculated by [(5*weekday hours)+(2*weekend hours)]/7. "Tutoring Hours" include after-school and private tutoring. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lastly, Table 2.6 and Figures 2.3 to 2.7 provide the event study results. While Table 2.6 reports all outcomes estimated by the discrete treatment model, Figures 2.3 to 2.7 present graphical representations of selected outcomes of interest. The estimates demonstrate a gradual decline in the duration of gaming, TV and/or video watching, as well as reductions in computer game intensity among heavy gamers comparing to light gamers. There is an initial decrease in cellphone game intensity in the first year of the policy implementation, but the impact does not last over time.

2.4 Conclusion

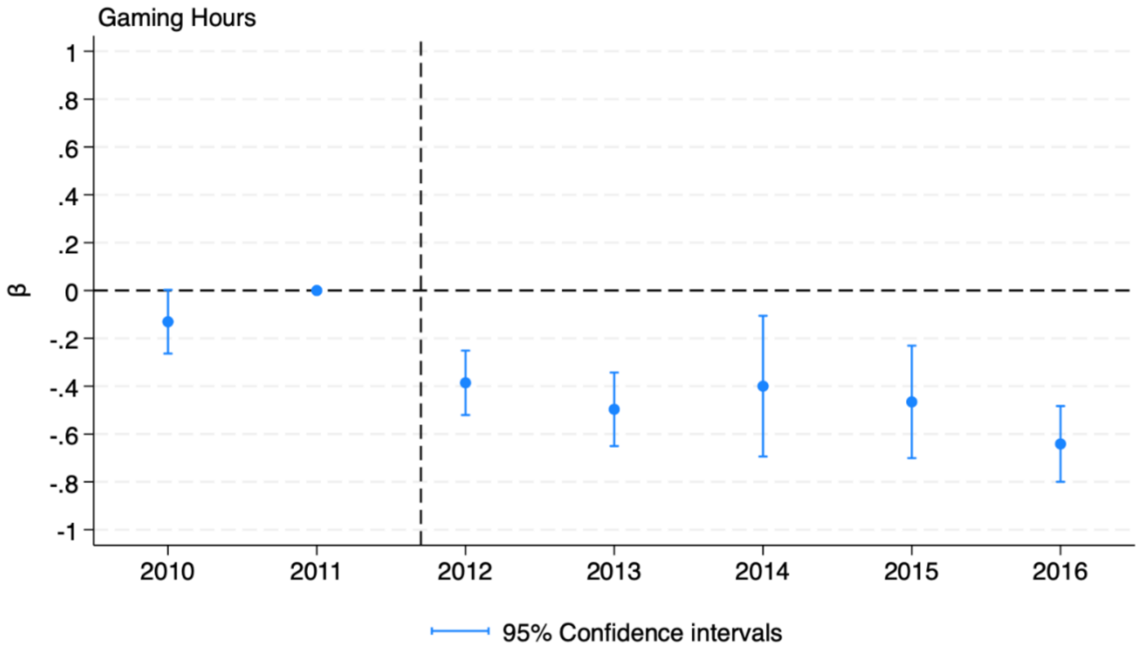
The implementation of the nationwide gaming shutdown policy in South Korea has thrust the nation into a pivotal role as a testing ground for a significant social experiment. The universal gaming shutdown policy has generated considerable debate and controversy in recent years, with different countries adopting varying approaches. A former South Korean President, Jae-In Moon, announced plans to repeal the "compulsive" shutdown policy by the end of 2021, while the “selective” shutdown policy remains in force (Kim & Chang, 2021; Hardawar, 2021). While the former policy has been repealed on December 31, 2021, the latter continues to be enforced at present. In contrast, China has recently implemented a stricter gaming ban, which prohibits online gamers under the age of 18 from playing games on weekdays (CNN Business, 2021).

This paper examines the impact of the gaming shutdown policy implemented in South Korea in 2012 on the students’ time allocation and behaviors. To enhance sleep patterns and minimize gaming addiction, the policy imposed limitations on children below 16 years old, prohibiting them from engaging in online games from midnight until 6am. Employing a difference in differences approach and using panel data from the Korean Children and Youth Panel Survey conducted from 2010 to 2016, I explore heterogeneous effects of the policy based on students’ prior gaming pattern. I find that heavy gamers, who were more likely to be affected by the policy, decreased the gaming hours by 25 minutes (26 percent of the base mean) while slightly increasing the reading hours by 6 minutes (7 percent of the base mean). In addition, the findings suggest that the shutdown policy reduced the intensity of computer game usage and cellphone game usage among individuals who were heavy gamers.

There are several limitations to this paper. First, this study relies on self-reported data. Survey participants may under-report or over-report their activities. Second, the data used in this study does not capture time use of all activities. While the KCYPS provides detailed information on how students allocate time each day, there are other activities that were not included in the data collection process. Therefore, the effects of the ban on time use are limited to a set of activities that were specifically included in the survey, like gaming, other computer activities and sleeping. Future studies could explore alternative data sources to gain a more comprehensive understanding of time use patterns. Additionally, there were challenges associated with implementing the shutdown policy. There are potential loopholes or exemptions which could impact its effectiveness. For instance, offline games and cellphone games are not regulated under the policy, which may limit its impact on overall gaming behavior. Moreover, the policy specifically targets late-night gaming, which may not fully address the broader issue of excessive gaming throughout the day. Given the findings that the policy had a considerable impact on reducing gaming hours among heavy gamers, one could consider alternative policy approaches such as expanding the scope of regulation or targeting specific gamers.

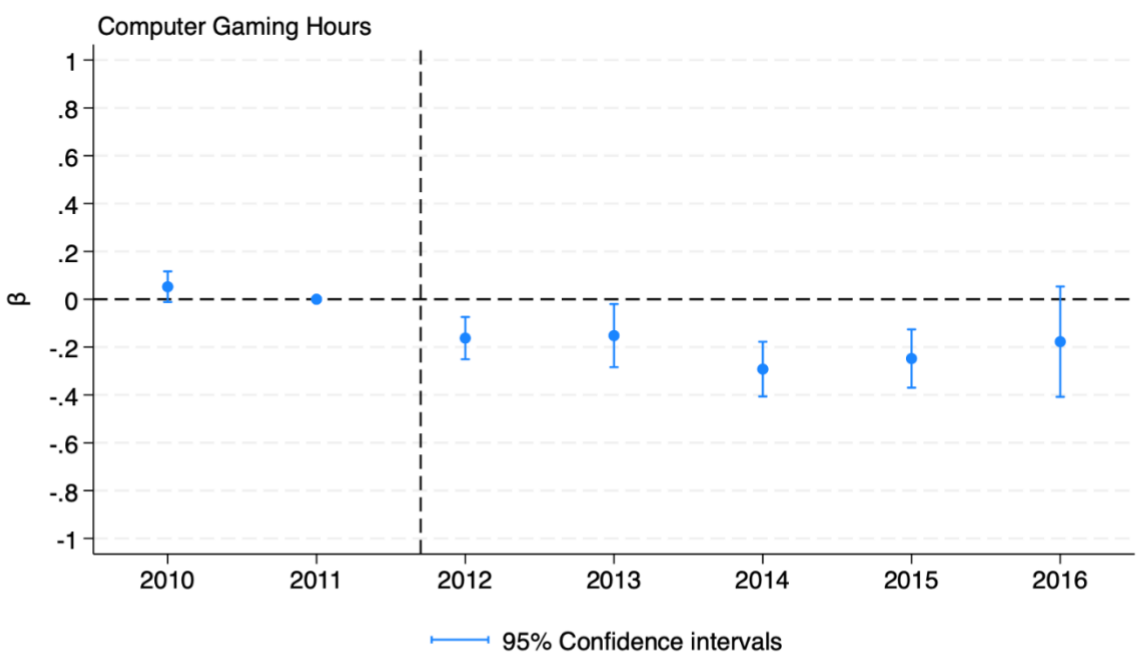
Despite these limitations, this paper contributes to the broader understanding of the gaming shutdown policy and its impact on the time allocation of young students. Further investigations in this area hold the potential to inform policymakers, educators, and parents in developing effective strategies and interventions to promote healthy time management and mitigate the potential adverse consequences associated with excessive gaming and gaming addiction.

Figure 2.4. Event Study Graph – Gaming Hours



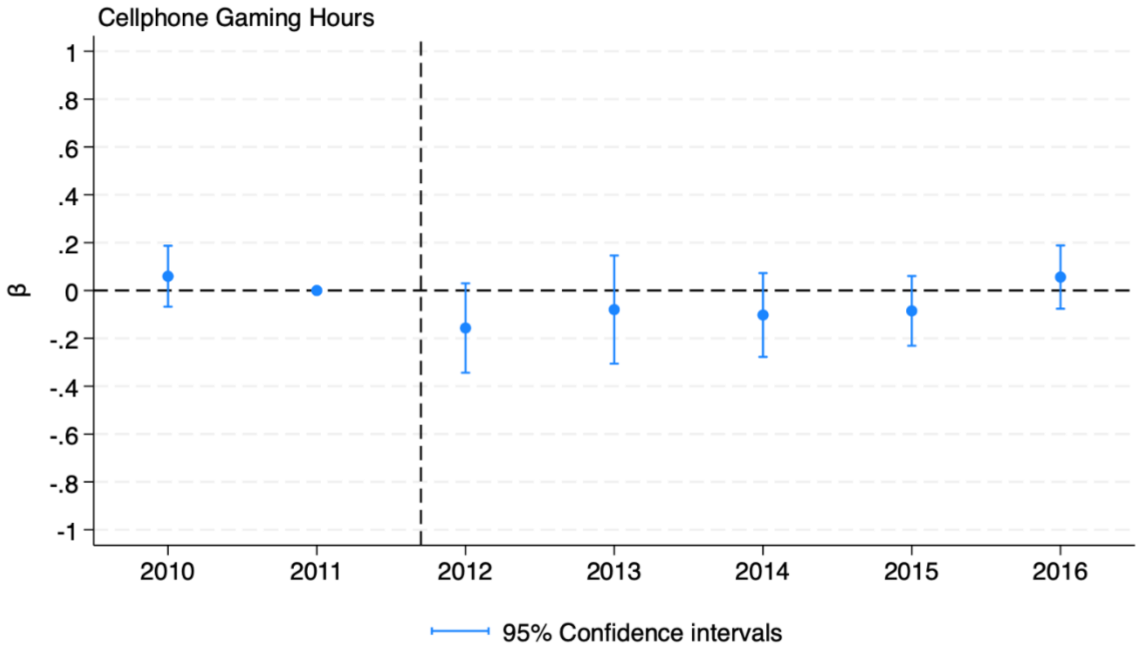
Source: KCYPS 2010-2016

Figure 2.5. Event Study Graph – Computer Gaming Intensity



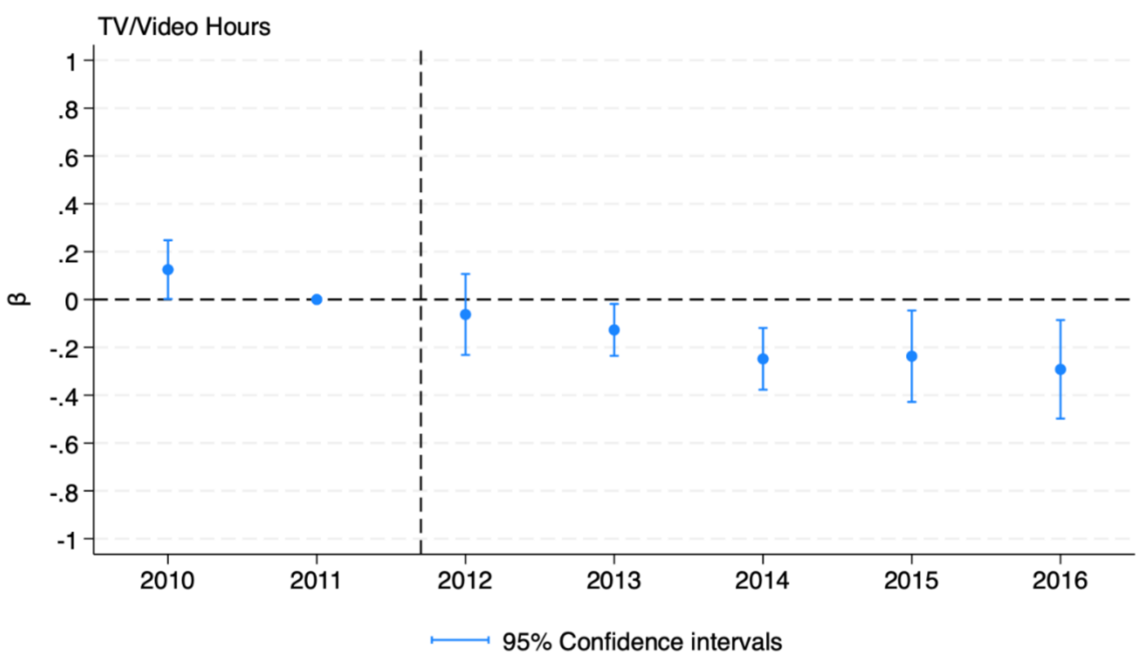
Source: KCYPS 2010-2016

Figure 2.6. Event Study Graph – Cellphone Gaming Intensity



Source: KCYPS 2010-2016

Figure 2.7. Event Study Graph – TV/Video Hours



Source: KCYPS 2010-2016

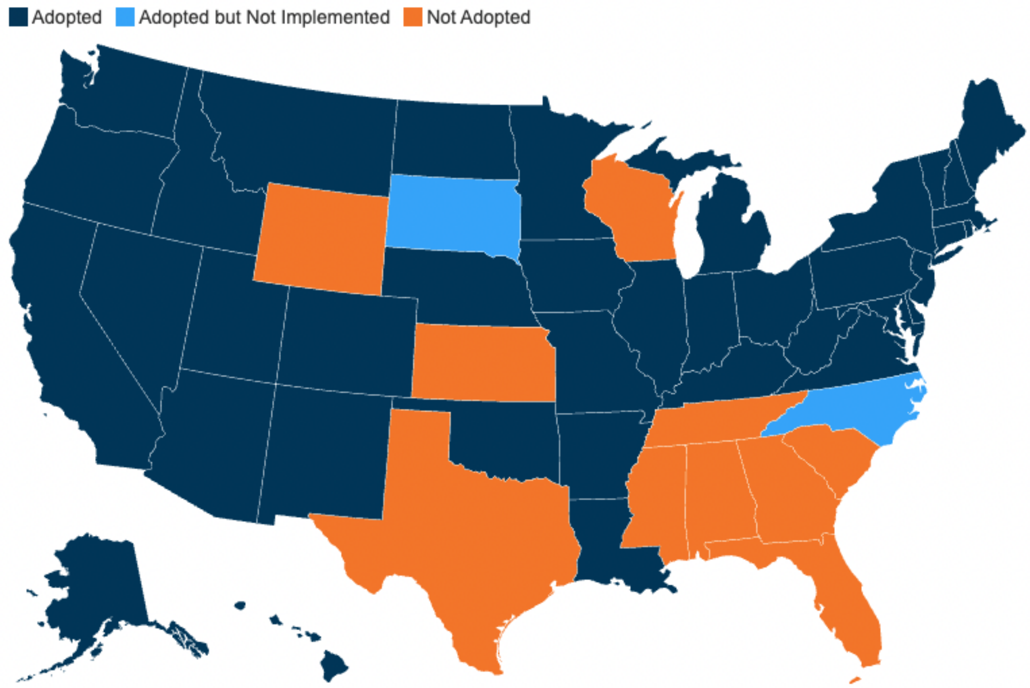
Chapter 3: Closing the Coverage Gap: The Impact of the ACA Medicaid Expansion on Low-Income Young Adults' Access to Health Insurance

3.1 Introduction

Young adults aged 19 to 34 in the United States have historically had the highest uninsured rates among all age groups (Kotagal et al. 2014; Conway, 2020). As an effort to expand health insurance eligibility and coverage among young adults as well as to the rest of the United States population, the Patient Protection and Affordable Care Act (ACA) was signed into law in 2010 (Blumenthal et al., 2015; AMA, n.d.). One of the key elements of the ACA was to expand Medicaid eligibility to adults with income up to 138 percent of the federal poverty level (FPL). The ACA was intended to increase access to healthcare for low-income individuals and families, by expanding eligibility criteria to include childless, non-disabled, and non-pregnant adults, who were historically excluded from the program, as well as extending coverage to low-income adults (Wherry & Miller, 2016). However, due to the Supreme Court's ruling in *National Federation of Independent Business v. Sebelius* in 2012, states were given the option to accept or decline the Medicaid expansion, resulting in a coverage gap for individuals with incomes below 100% of the FPL in states that did not expand Medicaid.

Low-income young adults, in particular, are a vulnerable population with significant healthcare needs. More than 30 percent of young adult trauma patients did not have health insurance, low-income young adults without health insurance coverage are less likely to receive rehabilitation care after hospitalization due to a traumatic injury, and more than 50 percent of deaths among young adults are caused by unintentional injury or homicide (Metzger et al. 2021). Yet, they often face barriers to accessing care due to their socioeconomic status (Nicholson et al. 2009). Although the "dependent coverage" provision of the ACA Medicaid expansion in 2010

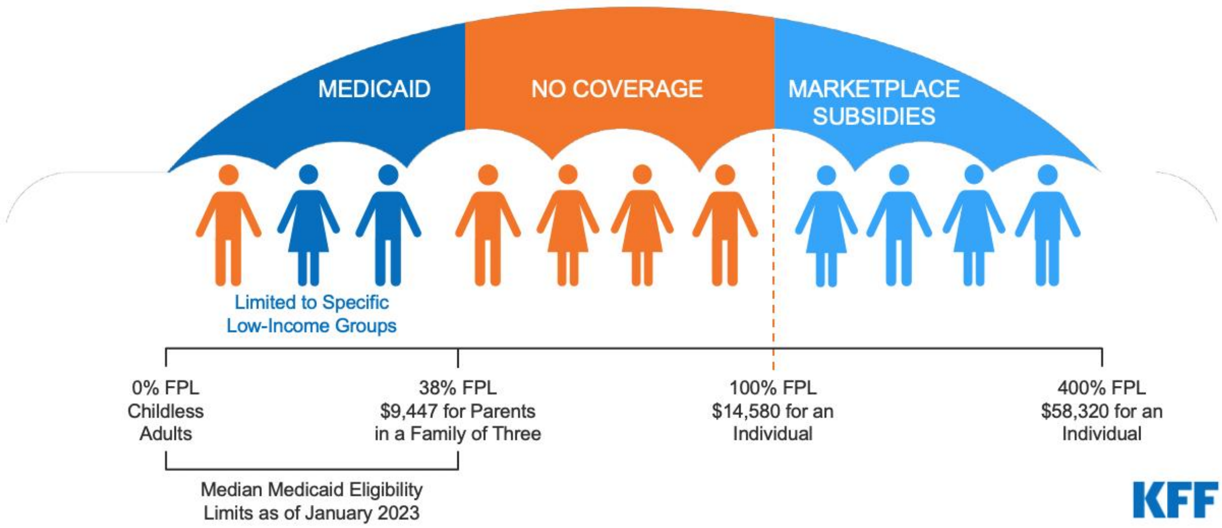
Figure 3.1. Status of State Action on the Medicaid Expansion Decision



Notes: Graph illustrates the status of state expansion decision on the Medicaid Expansion as of May 2023. Blue-shaded states are South Dakota (implementation contingent on appropriations in the SFY 2023-2024 biennial budget) and North Carolina (planned implementation for 7/1/2023) respectively. Retrieved from Kaiser Family Foundation (KFF) (https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/).

was intended to enhance health insurance coverage for young adults by extending coverage for dependents aged up to 26, this provision is likely to have a greater impact on young adults in middle- to high-income households since only dependents whose parents were covered by private health insurance could benefit from it (Gangopadhyaya & Johnston, 2021; Antwi et al. 2013; Cantor et al. 2012). Consequently, the ACA Medicaid expansion led to a gap in Medicaid coverage among young adults with low income, as illustrated in Figure 3.2. The Medicaid coverage gap refers to the situation where young adults with low income residing in non-expansion states are unable to meet the income eligibility criteria for both Medicaid and Marketplace coverage under the ACA Medicaid expansion. Specifically, those with income

Figure 3.2. Gap in Coverage for Adults in States Do not Expand Medicaid Under the ACA



Source: Kaiser Family Foundation (KFF). https://www.kff.org/medicaid/issue-brief/how-many-uninsured-are-in-the-coverage-gap-and-how-many-could-be-eligible-if-all-states-adopted-the-medicaid-expansion/

levels higher than the Medicaid eligibility threshold but lower than the income threshold for Marketplace subsidies are not eligible for either Medicaid or coverage purchased through Marketplace. According to an analysis conducted by the Kaiser Family Foundation (KFF) using data from the 2021 American Community Survey (ACS), approximately 3.5 million nonelderly adults fall into the Medicaid coverage gap, with half of this population consisting of young adults aged 19 to 34 (Rudowitz et al. 2023). This specific population of young adults holds the potential to gain health insurance coverage through the universal expansion of Medicaid eligibility.

There is a well-documented literature on examining the effects of the ACA Medicaid expansion on the overall population (Blumenthal et al., 2015; Wherry & Miller, 2016; Miller & Wherry, 2017; Kaestner et al. 2017). These studies have generally found that the expansion has had positive impacts on adults in expansion states, comparing to those in non-expansion states. Specifically, they have shown that the expansion has led to improvements in health insurance coverage, healthcare utilization, access to healthcare, health status, labor market outcomes, and educational outcomes. Although several studies have examined the ramifications of the ACA

Medicaid expansion on the general population, few recent studies have centered on evaluating the effects of the expansion specifically on low-income young adults. Gangopadhyaya and Johnston (2021) and Semprini et al. (2022) represent two of the most recent studies conducted on the subject. Gangopadhyaya and Johnston (2021) studies the impacts of the ACA Medicaid expansion on health insurance coverage and health care access among young adults aged 19 to 25 using 2011-2018 American Community Survey (ACS) and Behavioral Risk Factor Surveillance System (BRFSS). Semprini et al. (2022) examines the effect of the ACA Medicaid expansion on self-reported health status of low-income young adults aged 25 to 64 years over 5 years employing data from the BRFSS for years 2011 through 2018. While both studies provide comprehensive analyses of the impact of the expansion, two data limitations arise: information on exact household size is missing, and income is recorded in intervals, which makes it challenging to accurately determine individual income and identify young adults who fall into the Medicaid coverage gap. To address this, I utilize data from the March Current Population Survey (CPS) which provides exact income information, specifically in the form of Adjusted Gross Income (AGI), used to determine Medicaid eligibility.

This paper examines the impact of the ACA Medicaid expansion on the uninsured rate and Medicaid coverage rate of low-income, childless, non-disabled young adults who fall into the Medicaid coverage gap. Specifically, I aim to answer the following research questions: (1) what is the impact of the ACA Medicaid expansion on the health insurance coverage rate of poor young adults who fall within the Medicaid coverage gap? and (2) has young adults' coverage rate through group health insurance and private health insurance shifted following the expansion? To answer these questions, I conduct a series of quantitative analyses employing difference-in-differences (DID) and event study methods using the aforementioned data.

The subsequent sections of this paper are structured as follows: Section 2 provides a comprehensive overview of the ACA Medicaid expansion, with a specific focus on its implications for young adults. In the next two sections, I present data and empirical models I employ to conduct the analyses as well as the analyses results. The final section discusses the findings and concludes.

3.2 The Affordable Care Act (ACA) Medicaid Expansion and Young Adults

The Patient Protection and Affordable Care Act (ACA) of 2010, enacted on March 23, 2010, introduced fundamental legal safeguards that have been absent, providing a nearly universal assurance of affordable health insurance coverage spanning from birth to retirement (Rosenbaum, 2011). The Act aimed to broaden Medicaid eligibility criteria and increase access to healthcare coverage for low-income individuals in the United States. While Medicaid primarily covered specific groups such as children, pregnant women, and individuals with disabilities, states were given the option to extend Medicaid eligibility under the expansion to include adults with incomes up to 138 percent of the federal poverty level (FPL) taking effect in 2014 (Courtemanche et al., 2016).

Prior to the passage of the ACA Medicaid expansion in 2014, Medicaid eligibility criteria varied significantly across states. While Medicaid primarily provided coverage for certain groups such as children, pregnant women, parents, individuals with disabilities, and elderly adults, eligibility requirements and income thresholds varied widely. Specifically, states had discretion to determine Medicaid eligibility using their own income disregards, deductions, and asset tests[17]. However, the ACA shifted the eligibility criteria to a standardized methodology known as

[17] Disregards is an informal term that relates to a state Medicaid program's methodology for counting income and resources in determining eligibility. For certain eligibility categories, such as poverty-related children or working disabled adults – states may disregard certain income or resources in determining whether the individual meets its

Modified Adjusted Gross Income (MAGI), which eliminated the use of state-specific criteria (MACPAC, n.d.). This method simplified the application process but does not account for income disregards that vary by state or eligibility group, nor does it include an asset or resource test. As part of this shift, a single income eligibility disregard of 5 percent of the FPL was established, with effective eligibility set at 138 percent of the FPL, even though the federal statute specifies 133 percent FPL. MAGI is now used to determine eligibility for parents, children, pregnant women, and the new adult group, but individuals over 65 or those with disabilities continue to be determined using pre-ACA methods[18]. In addition to the financial criteria, individuals must meet non-financial criteria to qualify for Medicaid, such as residency and citizenship status. For example, they must be citizens or qualified aliens of the United States to receive the full range of benefits offered under the program. Some eligibility groups have additional restrictions based on age, pregnancy, or parenting status.

Due to several factors, young adults with low income faced limited eligibility for Medicaid coverage before and after the expansion. First, as described above, Medicaid traditionally provided coverage to specific groups. Young adults who did not fall into these specific categories are often excluded from the Medicaid coverage. Second, Medicaid eligibility was subject to income thresholds that varied by state. Many states set income limits that were significantly lower than the federal poverty level (FPL), making it difficult for poor young adults to qualify for Medicaid. Even after the expansion, those young adults in non-expansion states remained uninsured due to the low maximum income thresholds. Third, if they were not

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Medicaid income or resource standards. Refer to Medicaid Glossary from KFF: https://www.kff.org/wp-content/uploads/2013/05/mrbglossary.pdf

[18] No asset test applies to individuals whose income eligibility is based on MAGI, although states may still require an individual's assets to be below certain level to qualify for Medicaid on the basis of a disability or being 65 or older.

categorized as dependent children or their parents did not hold any eligible insurance to cover their child dependents, they were excluded from Medicaid coverage. As a result of these factors, many poor young adults fell into the so-called Medicaid coverage gap, where they did not meet the eligibility requirements for Medicaid, fell outside the scope of existing Medicaid criteria, were unable to afford private health insurance, of had incomes exceeding the threshold for qualifying for Marketplace coverage subsidies.

3.3 Methodology

3.3.1 Data

I use data from the March Current Population Survey (CPS) from calendar year 2010 through 2019 (survey year 2011~2020) for the analyses. The Current Population Survey (CPS) is the survey monthly administered by the U.S. Bureau of Census for the Bureau of Labor Statistics. The CPS collects data from a representative sample of households across the nation, covering a wide range of demographic and economic information. Specifically, the March CPS data provides detailed information on individuals' demographic, personal/family/household incomes, the AGI, health insurance coverage, and so forth.

I restrict the analysis sample to include U.S. citizens between the ages of 19 and 34 who are low-income, childless, non-disabled, and non-pregnant. With the detailed information on household size, individuals' AGI, and other relevant income variables, I can identify the young adults who have an AGI of 138 percent of less of the Federal Poverty Level (FPL)[19]. Tables 3.1 and 3.2 present summary statistics for the main analysis sample by treatment group as well as

[19] According to the U.S. Centers for Medicare & Medicaid Services (CMS), MAGI is adjusted gross income (AGI) plus these, if any: untaxed foreign income, non-taxable Social Security benefits, and tax-exempt interest. For most people, MAGI is identical or very close to adjusted gross income. Note that MAGI does not include Supplemental Security Income. Information retrieved from https://www.healthcare.gov/glossary/modified-adjusted-gross-income-magi/#:~:text=MAGI%20is%20adjusted%20gross%20income,Supplemental%20Security%20Income%20(SSI).

Table 3.1. Summary Statistics – All Sample, by Treatment Group

	Full Sample		Treatment States		Control States	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variables						
Uninsured	0.36	0.47	0.32	0.47	0.36	0.48
Covered by Medicaid	0.26	0.44	0.27	0.45	0.24	0.43
Covered by Group HI	0.12	0.32	0.11	0.32	0.12	0.32
Covered by Private HI	0.40	0.49	0.41	0.49	0.39	0.49
Independent Variables						
Food Stamp Recipiency	0.26	0.44	0.25	0.43	0.27	0.44
Age	23.47	4.37	23.46	4.38	23.47	4.37
Female	0.51	0.50	0.50	0.50	0.51	0.50
White	0.69	0.46	0.71	0.45	0.67	0.47
Black	0.21	0.41	0.16	0.37	0.26	0.44
Asian	0.05	0.22	0.07	0.25	0.04	0.18
American Indian / Pacific Islander	0.02	0.15	0.03	0.17	0.02	0.13
Married	0.05	0.23	0.05	0.22	0.06	0.24
Employed	0.39	0.49	0.40	0.49	0.39	0.49
Education > HS	0.82	0.39	0.83	0.38	0.80	0.40
Education > HS (Mother)	0.93	0.25	0.93	0.25	0.93	0.25
Education > HS (Father)	0.97	0.17	0.96	0.19	0.98	0.15
Observations	21,753		11,070		10,683	

Notes: Table above presents the sample summary statistics, each weighted by the individual weight provided from the data source. Analysis sample includes childless, non-disabled, non-pregnant low-income young adults (HH income < 100% FPL) over the period of 2010-2019 calendar years. Treatment states include expansion states, control states include non-expansion states. Details on assignment of treatment states and control states are described in Table 3.3.

Table 3.2. Summary Statistics – Pre-/Post-Expansion, by Treatment Group

	Pre-Expansion				Post-Expansion			
	Treatment States		Control States		Treatment States		Control States	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variables								
Uninsured	0.41	0.49	0.42	0.49	0.21	0.41	0.29	0.46
Covered by Medicaid	0.22	0.41	0.22	0.42	0.34	0.47	0.26	0.44
Covered by Group HI	0.11	0.31	0.11	0.31	0.12	0.32	0.13	0.34
Covered by Private HI	0.38	0.48	0.35	0.48	0.47	0.50	0.46	0.50
Independent Variables								
Food Stamp Recipiency	0.25	0.43	0.29	0.45	0.25	0.43	0.25	0.43
Age	23.33	4.31	23.40	4.40	23.62	4.46	23.54	4.33
Female	0.50	0.50	0.50	0.50	0.51	0.50	0.52	0.50
White	0.73	0.45	0.66	0.47	0.69	0.46	0.67	0.47
Black	0.16	0.36	0.26	0.44	0.16	0.37	0.26	0.44
Asian	0.06	0.23	0.04	0.20	0.08	0.27	0.03	0.17
American Indian / Pacific Islander	0.03	0.17	0.02	0.13	0.03	0.17	0.02	0.12
Married	0.05	0.22	0.07	0.25	0.05	0.21	0.05	0.22
Employed	0.39	0.49	0.39	0.49	0.41	0.49	0.39	0.49
Education > HS	0.82	0.38	0.78	0.41	0.84	0.37	0.83	0.38
Education > HS (Mother)	0.93	0.26	0.93	0.26	0.94	0.23	0.94	0.23
Education > HS (Father)	0.96	0.20	0.97	0.17	0.97	0.18	0.98	0.13
Observations	5,946		5,263		5,124		5,420	

Notes: Table above presents the sample summary statistics, each weighted by the individual weight provided from the data source. Analysis sample includes childless, non-disabled, non-pregnant low-income young adults (HH income < 100% FPL) over the period of 2010-2019 calendar years. Treatment states include expansion states, control states include non-expansion states. Details on assignment of treatment states and control states are described in Table 3.3.

pre- and post-policy periods. 34 percent of the analysis sample have no health insurance coverage (no Medicaid, group health insurance, or private health insurance coverages), while 26 percent are covered by Medicaid, 12 percent are covered by employment-based insurance plan, and 40 percent are covered by private health insurance. Young adults in the non-expansion states have higher uninsured rate, lower Medicaid coverage rate, and comparable group health insurance and private insurance coverage rates, compared to those in the expansion states. The majority of the analysis sample are white (69 percent) where racial composition of treatment and control states varies, and a greater portion of people in control states received Supplemental Nutrition Assistance Program benefits (aka "food stamps"). The rest of the characteristics are similar across the treatment and control states.

Following the approach taken by several previous studies, such as Kaestner et al. (2017) and Miller and Wherry (2019), I first classify states as expansion states if they adopted the expansion in 2014, including states that had a prior, but limited, expansion for parents and/or childless adults, in order to use 2014 as the first year of the post-expansion period. Therefore, I drop states that expanded Medicaid eligibility in 2015 or later[20]. Control states include: 1) states that never expanded Medicaid until the last day of 2019 (whether they had prior expansions for parents and childless adults or not), and 2) 5 states that expanded in 2014 but had prior full expansions for parents and childless adults. To check whether dropping the states with prior full expansions for parents and childless adults affect the results, I also estimate an alternative model excluding these states from the analysis sample and report the results. Detailed description of how I classify states as expansion and non-expansion states is tabulated in Table 3.3.

[20] This includes Alaska (9/1/2015), Indiana (2/1/2015), Louisiana (7/1/2016), Maine (1/10/2019), Montana (1/1/2016), Pennsylvania (1/1/2015), and Virginia (1/1/2019).

Table 3.3. Treatment and Comparison States

Comparison States			
No expansion in 2014		No expansion in 2014	Expansion in 2014
No prior expansion		Prior limited expansions for parents and/or childless adults	Prior full expansions for parents and childless adults
Alabama Alaska (9/1/2015)’ Florida Georgia Idaho (1/1/2020) Kansas Louisiana (7/1/2016)’ Mississippi Missouri^ (10/1/2021) Montana (1/1/2016)’ Nebraska (10/1/2020)	North Carolina* Oklahoma (7/1/2021) Pennsylvania (1/1/2015)’ South Carolina South Dakota* Texas Utah (1/1/2020) Virginia (1/1/2019)’ Wyoming	Indiana (2/1/2015)’ Maine^ (1/10/2019)’ Tennessee Wisconsin	Delaware Washington, DC Massachusetts New York Vermont

Treatment States		
Expansion in 2014	Expansion in 2014 Prior limited expansions for parents and/or childless adults	
Arkansas Kentucky Michigan (4/1/2014) Nevada New Hampshire (8/5/2014) New Mexico North Dakota Ohio West Virginia	Arizona California Connecticut Colorado Hawaii Illinois Iowa	Maryland Minnesota New Jersey Oregon Rhode Island Washington

Notes: States expanded Medicaid eligibility on 1/1/2014 unless noted otherwise in parentheses. *: adopted but not yet implemented. ^: Missouri coverage retroactive to 7/1/2021, Maine coverage retroactive to 7/2/2018. ‘: states dropped in the main analysis.

Figure 3.3. Raw Trend of Uninsured Rate by Treatment Group

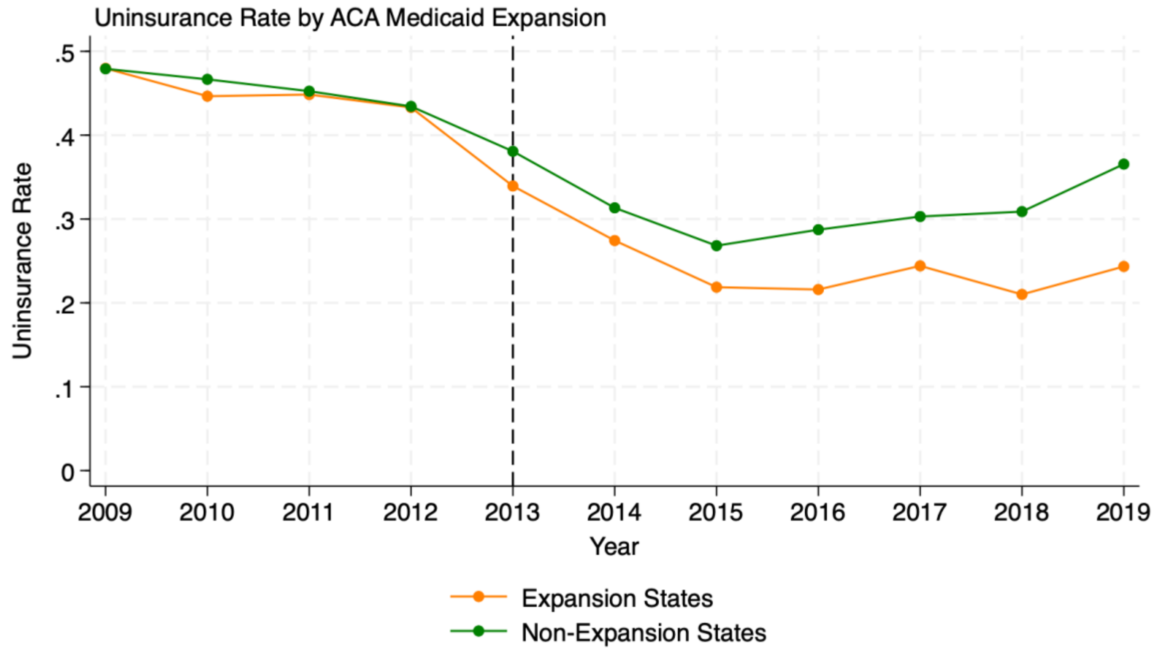


Figure 3.4. Raw Trend of Medicaid Coverage Rate by Treatment Group

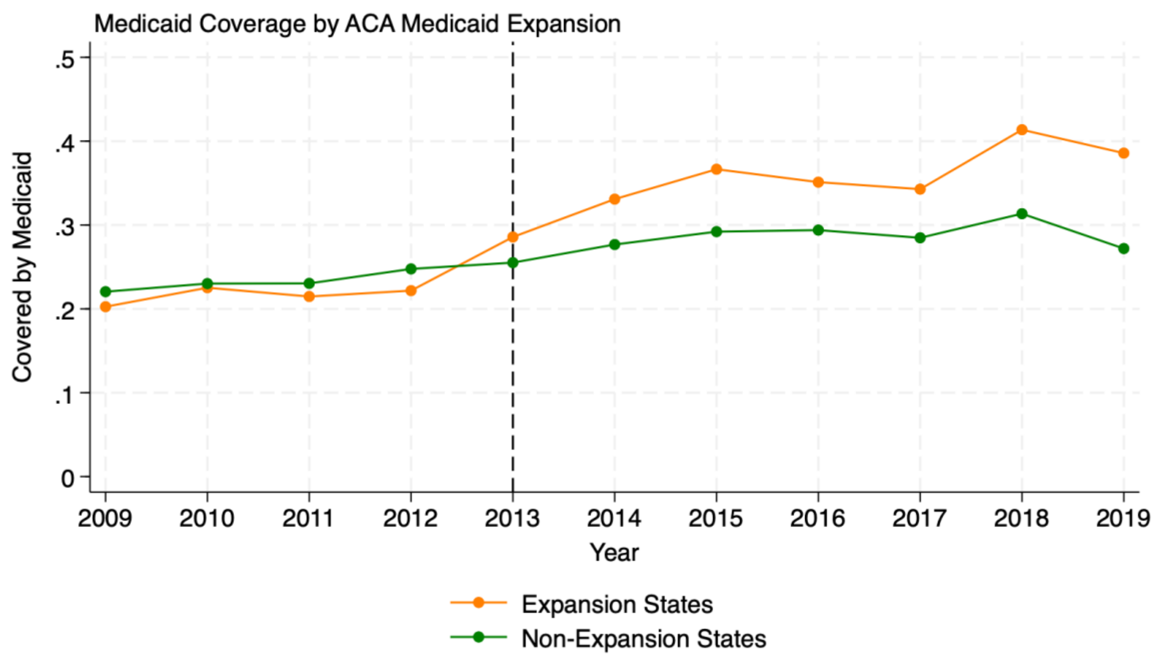


Figure 3.5. Raw Trend of Group Health Insurance Coverage Rate by Treatment Group

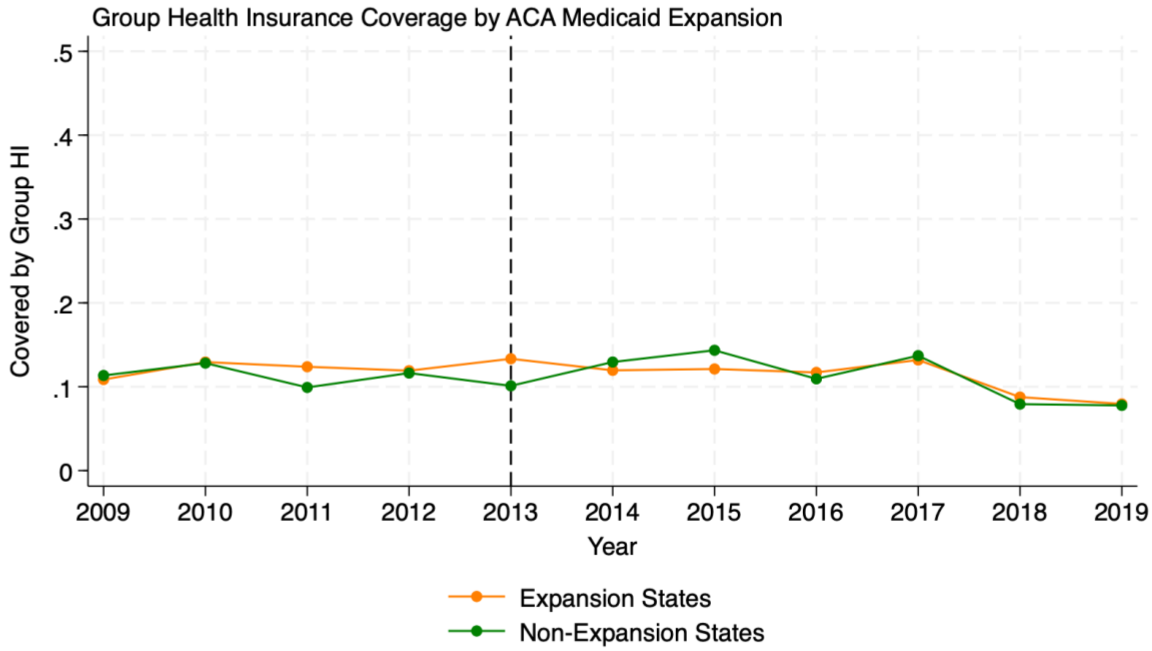
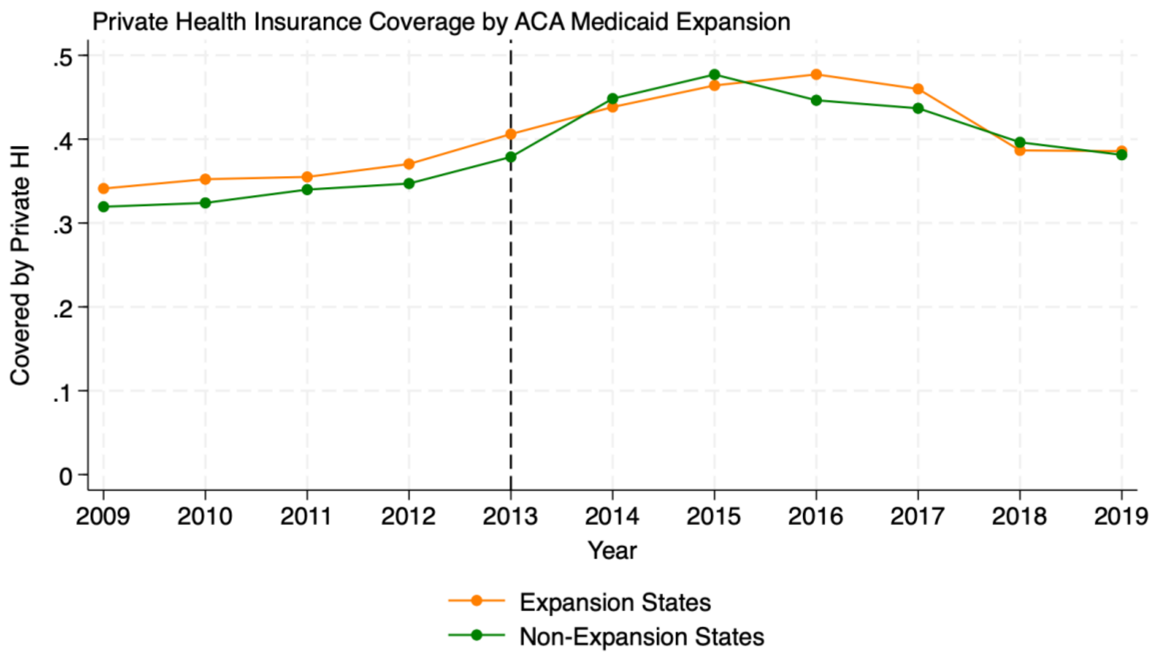


Figure 3.6. Raw Trend of Private Health Insurance Coverage Rate by Treatment Group



3.3.2 Empirical Model

To study the impact of the ACA Medicaid expansion on various health insurance coverage outcomes for young adults, I first estimate the following difference-in-differences regressions, comparing estimated outcomes for young adults within the coverage gap in the expansion and non-expansion states:

$$y_{ist} = \beta_0 + \beta_1 treat_{is} + \beta_2 post_t + \beta_3 treat_{is} \times post_t + \boldsymbol{\beta_4 X_{ist}} + \sigma_s + \tau_t + \epsilon_{ist} \quad (1)$$

where y_{ist} is health insurance coverage outcomes (uninsured rate, Medicaid coverage rate, group/private health insurance coverage rates) for an individual i living in a state s in a calendar year t[21]. $treat_i$ is a dummy variable that indicates whether the low-income, childless, non-disabled, non-pregnant young adult is in the treatment state, or the comparison state, as described in the previous section. $post_t$ is a dummy variable that indicates whether the current year is within the pre- or post-expansion period (0 for pre-2014, 1 for 2014 and onwards), and $\boldsymbol{X_{ist}}$ is a vector of time-varying individual characteristics, such as demographics, education, and other relevant factors. σ_s and τ_t refer to state and year fixed effects respectively. Lastly, ϵ_{ist} is an idiosyncratic error term, and standard errors are clustered at the state level. Our key coefficient is β_3, which is a difference-in-differences estimate of the effect of the expansion on young adults in the expansion states.

To investigate early and late effects of the expansion as well as pre-expansion parallel trends, I estimate the following event study model:

$$y_{ist} = \beta_0 + \sum_{t=2010}^{2019} \beta_t \tau_t \times treat_{is} + \boldsymbol{\beta_4 X_{ist}} + \sigma_s + \tau_t + \zeta_{ist} \quad (2)$$

[21] I replace group and private health insurance coverage rates (COVERGH and COVERPI in the CPS data) with PAIDGH (employer paid for group health plan) and PHINSUR (reported covered by private health insurance) in calendar year 2018 and 2019 since neither COVERGH nor COVERPI were not collected in the both calendar years.

where the notations are analogous with the DID model described above. I use 2013 (one year prior to the expansion) as the omitted year (year 0 in event time). The key coefficient is β_t, which allows one to test for the parallel trend assumption for the pre-treatment periods as well as to capture the impact of the expansion in each of the post-expansion years.

3.4 Results

The DID results of the main identification and the alternative identification (where I drop 9 control states that had prior limited or full expansions for parents and childless adults) are presented in Tables 3.4 and 3.5. The tables consist of four columns, each representing models with distinct outcomes. In Table 3.4, the treatment effect estimate presented in the first column indicates that the Medicaid expansion led to a significant reduction of approximately 7 percentage points (equivalent to 17 percent of the base mean of pre-expansion treatment group) in the uninsured rate of young adults in the expansion states, compared to those in the non-expansion states. This decrease in the uninsured rate can be attributed to the concurrent increase in Medicaid coverage rate among these young adults. Specifically, following the expansion, there was an increase of about 6 percentage points (equivalent to 30 percent of the base mean) in Medicaid coverage rate among young adults residing in the expansion states. There was no statistically significant impact on group health insurance coverage and private health insurance coverage rates. The findings of the alternative model identification demonstrate a consistent pattern with the main identification results, except that there is a decrease of about 3 percentage points in the rate of group health insurance coverage.

Tables 3.6 to 3.7 and Figures 3.3 to 3.6 present the event study results estimated from the main identification. Analogous to the structure of Tables 3.1 and 3.2, each column represents models with four distinct outcomes. Each row then represents the treatment effect for each year

Table 3.4. DID Results – Main Identification

	(1) Uninsured	(2) Medicaid	(3) Group HI	(4) Private HI
Treatment Effect	-0.0698***	0.0639***	-0.00542	0.00556
	(0.0200)	(0.0149)	(0.0145)	(0.0159)
Observations	0.41	0.22	0.11	0.38

Notes: Base mean is pre-expansion mean of treatment states. Robust standard error in parentheses, clustered at state level. * p<0.1 ** p<0.05 *** p<0.01.

Table 3.5. DID Results – Alternative Identification

	(1) Uninsured	(2) Medicaid	(3) Group HI	(4) Private HI
Treatment Effect	-0.0648***	0.0583***	-0.0269**	0.00461
	(0.0194)	(0.0143)	(0.0127)	(0.0191)
Observations	18,456	18,456	18,456	18,456

Notes: Robust standard error in parentheses, clustered at state level. The estimates are from the alternative identification where I drop 9 states that had prior limited or full expansion for parents and childless adults. * p<0.1 ** p<0.05 *** p<0.01.

during the analysis period, excluding the year 2013 which is the omitted year. While the results indicate no significant or concerning pre-expansion trends, the treatment effect on the uninsured rate begins to emerge from the year 2016, which is two years after the initial implementation of the expansion. On the other hand, Medicaid coverage exhibits an initial impact in the earlier year, fades over time, and resurfaces in the year 2019. When dropping 9 states from the analysis and re-running the event study model, there is little change in the results except for a decrease in group health insurance coverage rate in 2015.

Table 3.6. Event Study Results – Main Identification

	(1) Uninsured	(2) Medicaid	(3) Group HI	(4) Private HI
y2010=1 # treat1=1	0.00100	-0.00937	-0.0254	-0.00609
	(0.0335)	(0.0173)	(0.0191)	(0.0244)
y2011=1 # treat1=1	-0.0147	0.000372	0.0109	-0.000797
	(0.0308)	(0.0274)	(0.0198)	(0.0266)
y2012=1 # treat1=1	0.00332	-0.00358	-0.0197	-0.0176
	(0.0341)	(0.0209)	(0.0260)	(0.0351)
y2013=0	0	0	0	0
y2014=1 # treat1=1	-0.0148	0.0304	-0.0155	-0.0173
	(0.0323)	(0.0238)	(0.0195)	(0.0330)
y2015=1 # treat1=1	-0.0453	0.0842***	-0.0378	-0.0396
	(0.0390)	(0.0292)	(0.0312)	(0.0418)
y2016=1 # treat1=1	-0.0881***	0.0436	0.0118	0.0462
	(0.0275)	(0.0406)	(0.0216)	(0.0342)
y2017=1 # treat1=1	-0.0364	0.0347	-0.0236	0.00756
	(0.0405)	(0.0401)	(0.0261)	(0.0392)
y2018=1 # treat1=1	-0.0869***	0.0603	0.00737	0.0153
	(0.0320)	(0.0362)	(0.0228)	(0.0487)
y2019=1 # treat1=1	-0.150***	0.128***	-0.00709	0.00301
	(0.0361)	(0.0365)	(0.0205)	(0.0300)
Observations	21,753	21,753	21,753	21,753

Notes: Robust standard error in parentheses, clustered at state level. * p<0.1 ** p<0.05 *** p<0.01.

Table 3.7. Event Study Results – Alternative Identification

	(1) Uninsured	(2) Medicaid	(3) Group HI	(4) Private HI
y2010=1 # treat2=1	0.0104	-0.00989	-0.0266	-0.00926
	(0.0356)	(0.0201)	(0.0180)	(0.0286)
y2011=1 # treat2=1	-0.0436	0.0108	0.0229	0.0190
	(0.0328)	(0.0359)	(0.0159)	(0.0271)
y2012=1 # treat2=1	-0.0157	-0.000520	-0.00850	0.00107
	(0.0382)	(0.0239)	(0.0188)	(0.0388)
y2013=0	0	0	0	0
y2014=1 # treat2=1	-0.0376	0.0266	-0.0325	0.0127
	(0.0332)	(0.0257)	(0.0198)	(0.0322)
y2015=1 # treat2=1	-0.0525	0.0598**	-0.0754**	-0.0156
	(0.0506)	(0.0239)	(0.0312)	(0.0494)
y2016=1 # treat2=1	-0.0935***	0.0392	-0.00786	0.0438
	(0.0287)	(0.0397)	(0.0215)	(0.0399)
y2017=1 # treat2=1	-0.0199	0.0183	-0.0316	0.00656
	(0.0445)	(0.0407)	(0.0270)	(0.0421)
y2018=1 # treat2=1	-0.0896**	0.0981***	-0.00658	-0.0251
	(0.0364)	(0.0303)	(0.0237)	(0.0390)
y2019=1 # treat2=1	-0.157***	0.117***	-0.0198	0.0162
	(0.0364)	(0.0380)	(0.0174)	(0.0341)
Observations	18,456	18,456	18,456	18,456

Notes: Robust standard error in parentheses, clustered at state level. The estimates are from the alternative identification where I drop 9 states that had prior limited or full expansion for parents and childless adults. * p<0.1 ** p<0.05 *** p<0.01.

Figure 3.7. Event Study Graph – Uninsured Rate

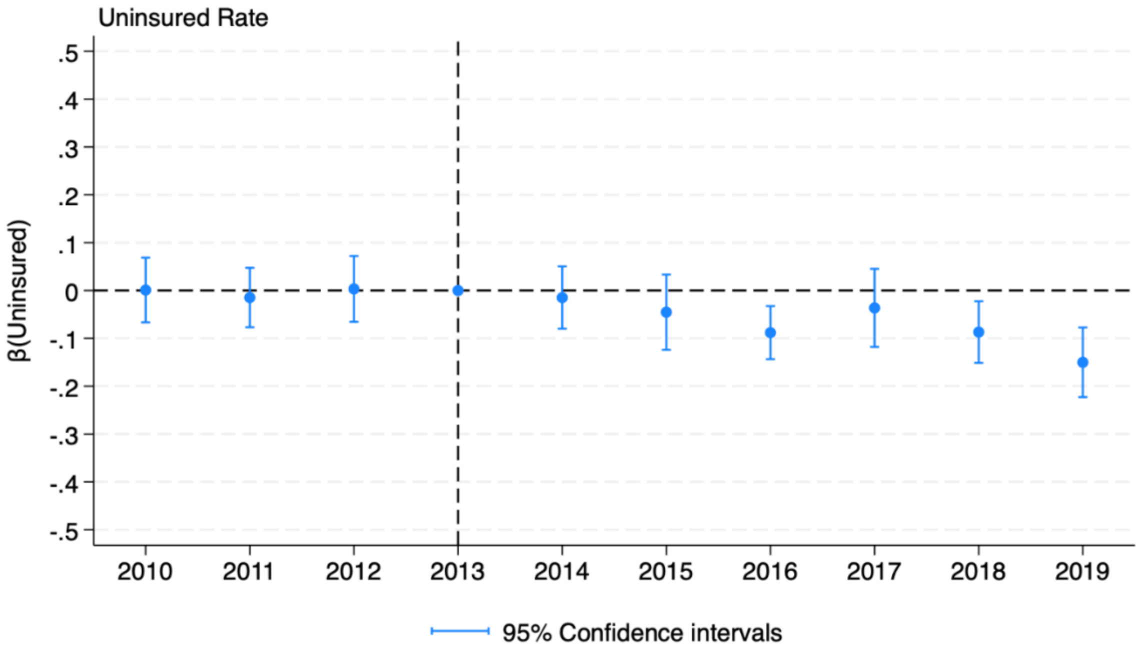


Figure 3.8. Event Study Graph – Medicaid Coverage Rate

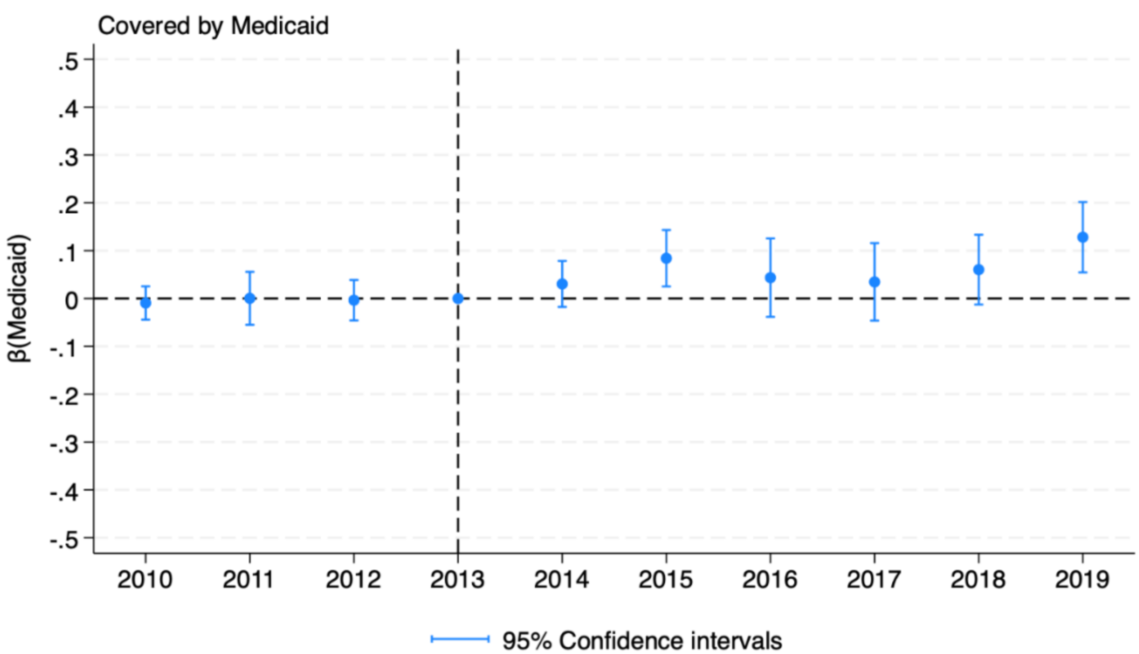


Figure 3.9. Event Study Graph – Group Health Insurance Coverage Rate

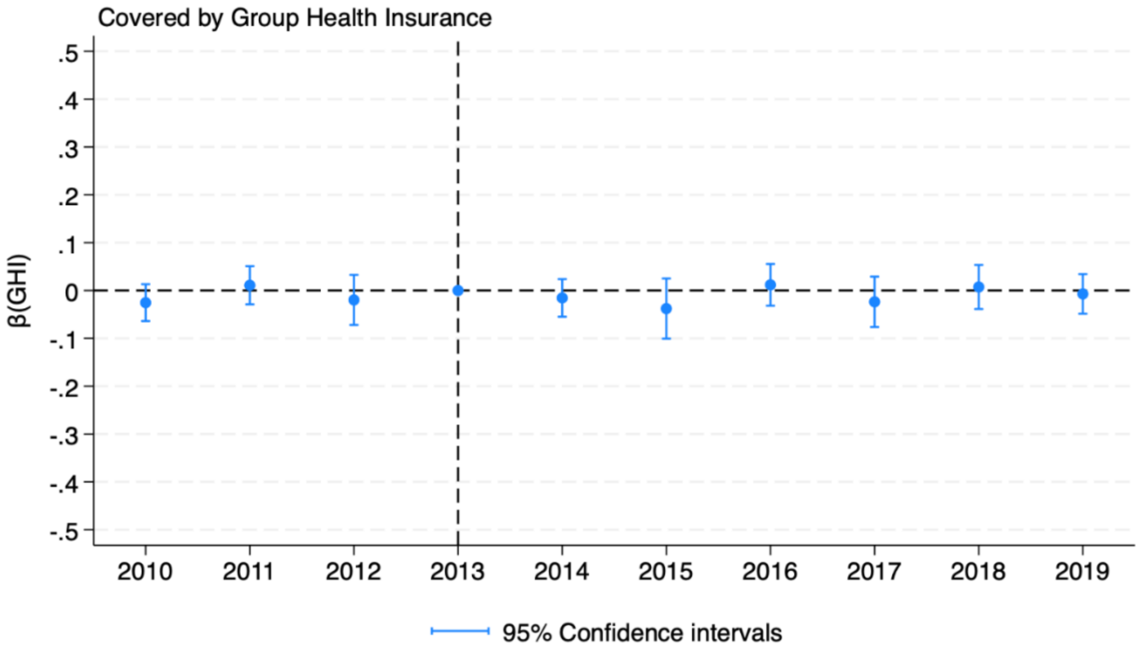
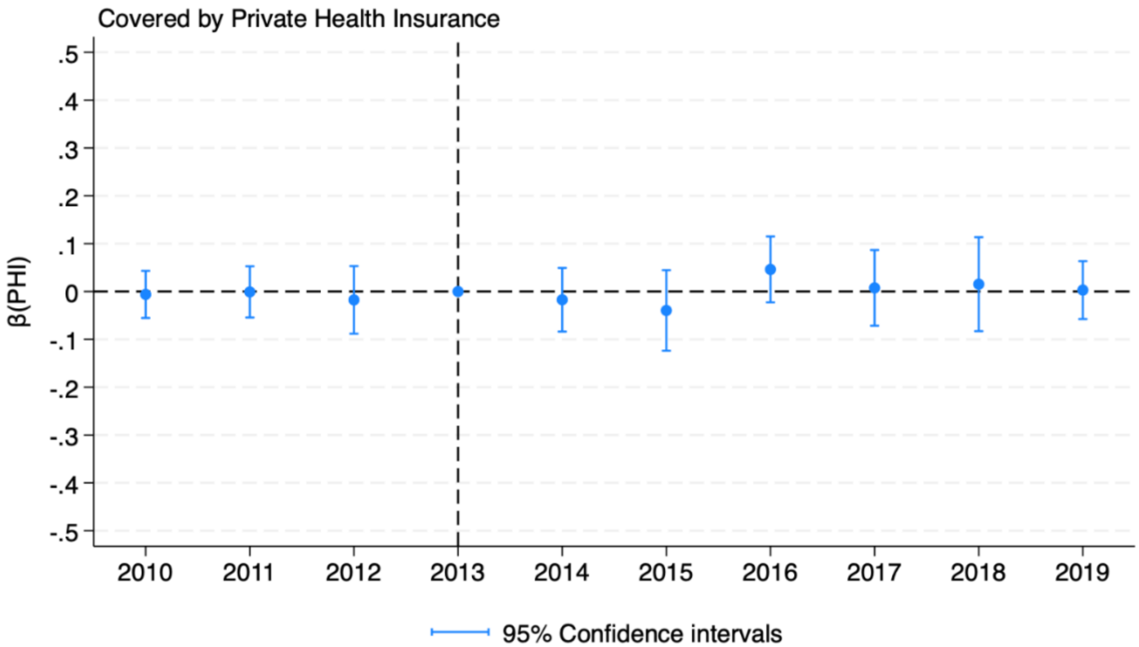


Figure 3.10. Event Study Graph – Private Health Insurance Coverage Rate



3.5 Conclusion

The implementation of the ACA Medicaid expansion has emerged as a significant endeavor in addressing healthcare disparities, particularly concerning the uninsured rate among low-income individuals. This paper illuminates the impact of this transformative policy on closing the coverage gap among low-income young adults and offers valuable insights into the potential future policy interventions to mitigate healthcare disparities.

This paper studies the impact of the ACA Medicaid expansion on the health insurance coverage of low-income, childless, non-disabled, and non-pregnant young adults who fall into the Medicaid coverage gap. The results indicate that the ACA Medicaid expansion had a positive impact on the health insurance coverage rate of poor young adults who fell within the Medicaid coverage gap. The difference-in-differences regression analyses showed that young adults in expansion states experienced a significant increase in Medicaid coverage and a decrease in uninsured rate compared to those in non-expansion states. This finding suggests that the expansion effectively expanded access to health insurance for this vulnerable population.

Moreover, the study examined whether the young adults' coverage rate through group health insurance and private health insurance shifted following the expansion. The results from the main identification showed no significant changes in rates of group health insurance coverage and private health insurance coverage. Finally, the event study analysis provides additional insights into the timing and magnitude of the effects of the expansion. The results showed a gradual increase in Medicaid coverage rates and decrease in uninsured rate among young adults in expansion states in the years following the implementation of the expansion. This finding is in line with previous work, indicating that the effects of the expansion are increasing over time, with the most significant impacts observed three to four years after the implementation (Miller & Wherry, 2019, among others).

Overall, the findings emphasize the importance of expanding Medicaid eligibility in all states to address the healthcare needs of young adults currently in the Medicaid coverage gap. Moving forward, it is imperative to prioritize additional research and policy initiatives aimed at identifying effective strategies to bridge the Medicaid coverage gap among vulnerable young adults.

Appendix A. Supplemental Tables and Figures

Table A1. School Reopening Matrix of the District

	Universal Remote	Phase I	Phase II	Phase III	Phase IV	Face-to-Face
Criteria to begin Phase		The district plans to move to Phase I of Universal Remote on September 8 to support our students' needs.	The district intends to use the Fulton County Board of Health epidemiology report to determine next steps. The district will begin to transition to the next phase of opening when three consecutive reports show a decline in the New Diagnosis Rate (per last 14 days) of cases per 100,000 OR County-wide New Diagnosis Rate is less than 175 (per last 14 days) per 100,000	The district intends to use the Fulton County Board of Health epidemiology report to determine next steps. The district will begin to transition to the next phase of opening when three consecutive reports show a decline in the New Diagnosis Rate (per last 14 days) of cases per 100,000 OR County-wide New Diagnosis Rate is less than 150 (per last 14 days) per 100,000	The district intends to use the Fulton County Board of Health epidemiology report to determine next steps. The district will begin to transition to the next phase of opening when three consecutive reports show a decline in the New Diagnosis Rate (per last 14 days) of cases per 100,000 OR County-wide New Diagnosis Rate is less than 125 (per last 14 days) per 100,000	The district plans to move to Face-to-Face instruction after the county-wide New Diagnosis Rate is less than 100 per 100,000 cases (per last 14 days)
Pre-K–2	All remote		½ Day (1 day per week)	1 Full Day (1 day per week)	2 Full Days (M/W or T/R)	5 Days
Sp. Ed.	All remote		½ Day (1 day per week)	1 Full Day (1 day per week)	2 Full Days (M/W or T/R)	5 Days
3–12	All remote	1:1 by Appointment	½ Day (1 day per week)	1 Full Day (1 day per week)	2 Full Days (M/W or T/R)	5 Days

Notes: Phase-on to Face-to-face was optional for parents. Data are reviewed on three-week cycles to determine phase. These data are leading indicators. The district monitored more than COVID-19 county data, including the impact of such data.

Table A2. List of Disciplinary Incident Codes

Incident Code	Incident Type	Frequency	Incident Code	Incident Type	Frequency
0	Continuation of Incident	4,185	22	Weapons – knife^	96
1	Alcohol	89	23	Weapons – other^	132
2	Arson	15	24	Other Discipline Incident^	3,096
3	Battery^	3,077	25	Weapons – handgun^	17
4	Burglary	61	26	Weapons – rifle^	1
5	Computer Trespass	4556	27	Serious Bodily Injury^	80
6	Disorderly Conduct^	7,964	28	Other firearms	0
7	Drugs, except Alcohol and Tobacco	657	29	Bullying^	447
8	Fighting^	4,927	30	Other – Attendance Related	3,847
9	Homicide	0	31	Other – Dress Code Violation	48
10	Kidnapping	0	32	Academic Dishonesty	557
11	Larceny or Theft	549	33	Other – Student Incivility^	6,141
12	Motor Vehicle Theft	0	34	Other – Possession of Unapproved Items^	281
13	Robbery	14	35	Gang-Related^	97
14	Sexual Battery^	24	36	Repeated Offenses	140
15	Sexual Harassment^	221	40	Other Non-Disciplinary Incident	214
16	Sex Offenses^	172	42	Electronic Smoking Device*	0
17	Threat or Intimidation^	1,695	44	Violence Against a Teacher*	0
18	Tobacco	727		Total	40,706
19	Trespassing	91			
20	Vandalism	488			

Note: The table shows a list of disciplinary incident codes and frequency of each incident type during SY 2018-19 and SY 2019-20 (incidents prior to the initial school closure) from the district's Student Disciplinary data.
^: I identify a student as "disruptive" if the student's incident falls into one of these disciplinary incidents.
*: These disciplinary incidents were newly listed in GaDOE Discipline Matrix table but none of the students in the analysis sample.

Table A3. Frequency of Pre-Pandemic Disciplinary Incidents by Student

Number of Incidents	Frequency	Percent	Cumulative Percent
0	12,080	35.35	35.35
1	6,216	18.19	53.55
2	3,846	11.26	64.80
3	2,658	7.78	72.58
4	1,932	5.65	78.23
5	1,482	4.34	82.57
6	1,139	3.33	85.91
7	884	2.59	88.49
8	689	2.02	90.51
9	553	1.62	92.13
9<		7.87	100.00

Note: Table above shows a frequency of disciplinary incidents by student from the analyses sample from SY 2018-19 to SY 2019-20.

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Vita

Sungmee Kim is an applied microeconomist with broad research interests broadly lie in education and health economics. She holds a bachelor's degree in international trade & logistics from Pukyong National University in South Korea and a bachelor's degree in economics from Georgia College & State University. She is currently a Ph.D. Candidate in Economics at Georgia State University, where she has worked as a Graduate Research Assistant at Georgia Policy Labs. Upon the completion of her Ph.D. in Economics degree at Georgia State University, she will be joining Samuel DuBois Cook Center on Social Equity as a Postdoctoral Associate starting in July 2023 to continue pursuing her research in the areas of K-12 education and health policy.