The Effects of COVID-19 Vaccines on the Health and Educational Outcomes of Children: Evidence from New York City Public Schools

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Abstract

COVID-19 vaccines emerged as a critical public health intervention for keeping schools safe and open, notably demonstrated in various clinical trials to show high effectiveness in protection from severe outcomes. However, the real-world impact of vaccinations beyond experimental settings remains less clear. The study examines the effects of vaccines on the health and educational outcomes among public school students in New York City during the 2021-2022 school year, when schools returned to in-person instruction. Combining a wide variety of administrative, clinical and monitoring data sources, I constructed a student-level dataset with information on standardized test scores, vaccines records, Medicaid claims, and their neighborhood-level factors. Employing an Instrument Variable and Difference-in-differences design, I leveraged the natural experiment of the age-based eligibility rule that granted one of two closely aged groups vaccine eligibility almost 6 months earlier. Among the 54,538 students with varied eligibility due to their birth month, early eligibility increased the school-year full vaccination rate by 24 percentage points and days spent fully vaccinated by 60.3 days. COVID-19 vaccine uptake increased standardized math scores, and reduced outpatient visits, COVID-19 infections and COVID-related ED visits. The protective effects of vaccines persisted over time and were most pronounced during periods of high community infection rates. While the effects of vaccines vary by race, ethnicity, and borough of residence, our study provides evidence that COVID-19 vaccines offer substantial benefits in a school setting and suggests that age-based vaccine distribution could lead to persistent, long-term disparities in vaccine uptake among students close to the cutoff.

Keywords: Vaccines, COVID-19, Children health, Education

JEL Codes: I18, I20

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Introduction

The COVID-19 pandemic had profound implications on all aspects of our society, leading to unprecedented mortality and morbidity, with a particularly devastating impact on minority, vulnerable, and lower-income populations (Lopez et al., 2021; Tai et al., 2021). Children's experiences mirror those of adults, as evidenced by impactful disruptions to their development, social interactions, and learning due to illnesses and school closures (Artiga et al., 2021). In New York City (NYC), a microcosm of urban challenges and disparities, these disruptions are amplified. Upon the resumption of in-person schooling in the 2021-2022 school year, emerging evidence highlights the pandemic's lingering impact on academic achievement (Mervosh, 2022). Therefore, keeping schools safe and open becomes a critical step toward recovery, particularly for underprivileged families who rely on school resources (Martin and Sorensen, 2020). Students, however, continue to face elevated risks in high-density environments, such as classrooms and public transportation. The challenging landscape in NYC underscores a pressing need for sustained interventions and policy responses, given the far-reaching developmental implications that could influence upcoming generations' productivity and health equity.

With the ongoing COVID-19 pandemic, it is essential to take all necessary precautions to ensure the safety of students and staff when reopening schools. Vaccination against COVID-19 is one of the most crucial public health interventions that can significantly reduce the risk of infection and ensure a safer learning environment for everyone. Drawing from a diverse population, clinical trials provided evidence for the vaccine's high effectiveness in preventing infection and serious illnesses (Barda et al., 2021; Oliver et al., 2022). Such protective effects potentially extend beyond individuals and to increases of uptake for other types of vaccines, given the beneficial spillover effects of the vaccines (Carpenter and Lawler, 2019). However, despite the high adult vaccination rate in NYC, the vaccination rates among children are relatively low - nearly half of NYC's children (NYC Department of Health, 2022) remained unvaccinated as of late 2022. This leaves unvaccinated children at a higher risk of illness, or severe outcomes (Dorabawila et al., 2022), and potential long-term adverse outcomes (e.g., MIS-C or long COVID), which are detrimental to their overall wellbeing and learning (Zimmermann et al., 2022; Shekerdemian et al., 2020; Levy et al., 2022). Moreover, the considerable disparity in child vaccination rates across racial, ethnic, and borough lines (Elbel et al., 2022) in NYC points to a multifaceted public health and policy challenge. These disparities, rooted in variations in population density, socioeconomic status, and access to healthcare, have led to exacerbated health outcomes for minority students, which also spilled over into their educational outcomes, as observed in the pandemic's trajectory (Kuhfeld et al., 2020; Mackey et al., 2021; Millett et al., 2020).

Addressing this challenge posed by the combination of continued risks of COVID-19 infection and suboptimal vaccination coverage requires a closer examination of the real-world effects of the COVID-19 vaccine, moving beyond controlled settings. This study examines the effects of vaccines among NYC public school students. As with other observational studies, this research provides several key features that complement and extend the insights from the clinical trials. Distinctly, the vaccine effectiveness derived from experiments might not translate to that of the real world due to behavioral changes (e.g., risk compensations and increased socialization) and the evolving nature of the virus. Furthermore, the context-specific evidence (such as in schools or nursing homes) on vaccine effectiveness is instrumental for policy formulation. Such insights could facilitate adaptive and targeted responses to promote vaccine uptakes or health and could inform a better cost-benefit analysis of these initatives. Additionally, observational studies shed light on COVID-related health disparities, as they can better capture the implications of vaccine hesitancy and systematic differences in resources that are difficult to account for in an experiment.

However, existing observational studies are limited in their ability to disentangle the endogeneity of one's vaccination decision. For example, (Lin et al., 2022), suggests vaccine uptake leads to better health outcomes, yet this link may be confounded due to the self-selection into vaccine uptake (Angrist and Pischke, 2008). People who seek vaccines proactively could inherently have higher motivations and awareness, alongside broader socioeconomic differences, as observed in studies on vaccine uptake (Gray and Fisher, 2022; Joshi et al., 2021). Aside from this fundamental methodological issue, no studies so far, to the best of my knowledge, examines the effect of COVID vaccines on non-health related outcomes among children that are crucial to their growth and development, such as educational outcomes.

To fill in this gap of research, the study aims to examine the effects of vaccines on both health and educational outcomes of NYC public school students enrolled in Medicaid. I address the issue of selection bias in vaccination decisions, described above, by leveraging the quasi-experiment of the age-based vaccine eligibility rule. Specifically, the US Food and Drug Administration (FDA) authorized the emergency use of Pfizer-BioNTech COVID-19 vaccine for children in the 12-15 age group in May 2021. Thus, students aged 12 and above became eligible, while the slightly younger students did not immediately. The younger children could either age into eligibility or wait until November 2021 when the vaccines for the 5-11 age group was authorized. This age-based rule of vaccine eligibility created a temporary yet sharp difference in eligibility for children around the 12-year-old cutoff. To examine the effects of vaccine uptake on health and educational outcomes, I linked multiple administrative data sources. The datasets encompass student enrollment files, educational records, school information, Medicaid insurance claims, and vaccination records, collectively forming a comprehensive database on student education-health information.

Comparing students 12 to 12.5 years old who became eligible earlier to 11 to 11.5 years old who had to wait until November, I found considerable differences in vaccine uptake. Specifically, early eligibility led to an increase in the probability of full vaccination by 24 percentage points and an additional average of 60 days being fully vaccinated, from the time vaccines were released up to the end of the 2021-2022 school year. Notably, this difference in vaccine uptake between the early and late eligibility groups persisted over time, with a gap of 13 percentage points remaining two years after the initial vaccine release.

Utilizing an Instrumental Variable (IV) and Difference-in-differences (DID) framework, I used early eligibility as an instrument for student vaccination status and measures of subsequent duration of vaccine protection during the 21-22 school year. The findings indicate that early eligibility and subsequent higher vaccine uptake reduced the number of sick days and boosted academic performance in math, though it had less of a consistent positive impact on reading. Additionally, I found strong evidence that vaccines protected various health outcomes of students. In the longitudinal analysis, vaccine uptake decreased the probability of any outpatient visits by 2.8 percentage points – a 40 % decrease compared to overall mean of the period, COVID infections by 0.3 percentage points – a 60% decrease, and COVID-related Emergency Department (ED) visits by 0.1 percentage points – a 100% decrease. These protective effects were most pronounced during periods of high community COVID-19 infection rates. These results remain robust to alternative definitions of early eligibility and model specifications. Additionally, the study identified heterogeneous effects across different demographic and geographic subgroups, in which the pandemic had differential impacts. Specifically, Black and White students and residents of Manhattan and Staten Island experienced more pronounced benefits from vaccination. Conversely, neighborhoods in the lowest quartile of cumulative infection rates experienced less pronounced protective effects.

The study, set in the context of the U.S.'s largest school district during its first fully in-person school year in the post-pandemic era, makes the following contributions. First, this paper quantifies the effects of vaccines in a real-world setting by leveraging a quasi-experimental design, thereby augmenting clinical trial findings with crucial context-specific insights. The results are vital for assessing the health and safety of children in a time of crisis, including the differential impacts across racial groups and geography. Second, this is the first study, to the best of my knowledge, that extends the examination of outcomes to educational outcomes, in addition to a broader range of health conditions than previously studied (Aslim et al., 2023; Freedman et al., 2022; Frenck et al., 2021), allowing us to verify vaccines' multifaceted benefits for a low-income population. Third, the study offers a nuanced understanding of the dynamic impacts of vaccinations over time. It considers the implications possibly due to the significant shift in public behavior, risk perception, and the rise of pandemic fatigue throughout the pandemic (Petherick et al., 2021; Qin et al., 2021). Additionally, the study provides insights into vaccine efficacy during periods of heightened infection rates, exemplified by the initial Omicron wave in NYC at the end of 2021. Lastly, the findings extend beyond the pandemic context, as they relate to the human behavior regarding the adoption of novel medical innovations in a time of crisis, further complicated by a surge in COVID-related misinformation and the unprecedented uncertainties facing the families (Loomba et al., 2021). These advancements address significant gaps in current research and offer vital insights for policies mitigating the continued impact of the pandemic on a critical population and bolster the preparedness of potential future disease outbreaks.

This study provides estimates for the effects of vaccines on student health and education wtih data from a school setting. The protective effects of vaccines go beyond preventing illness to also improve academic performance, affirming the strong connection between children's health and other crucial outcomes, such as human capital accumulation. The results highlight the far-reaching protective effects of vaccines in real-world settings and the promise of vaccines to support children's well-being during a time of crisis.

Backrgound

Clinical Trials and Real-World Implications

Clinical trials demonstrated the safety and efficacy of COVID vaccines in preventing infections, severe illnesses, hospitalizations, and deaths among both children and adults, drawing samples from populations with diverse demographic and medical profiles (Bergman et al., 2021; Thomas et al., 2021; Polack et al., 2020; Walter et al., 2022; Frenck et al., 2021). However, while these trials provide unbiased estimates of vaccine effectiveness within their study samples, their applicability to specific populations or settings is constrained by several important factors. First, non-compliance in the absence of a vaccine mandate challenges the external validity of the experimental results. To truly understand vaccine effectiveness at a population level, it is imperative to consider the actual rates of vaccine uptake, which may differ markedly across different regions and demographic groups (Barry et al., 2021). Moreover, people who are willing to vaccinate may be fundamentally different from those who are not (Angrist and Pischke, 2008), raising concern about the heterogeneous effectiveness of vaccines. Recent studies indicated that vaccinated individuals tend to have higher income and education levels, are less likely to belong to marginalized communities, and differ in other unobserved factors such as risk averseness and lifestyles (Joshi et al., 2021; Viswanath et al., 2021). The clinical trials focus on the comparative effectiveness of a randomized treatment therefore do not assess the implications of the systematic factors influencing vaccine uptake in a real world setting. These factors include trust in healthcare authorities (Razai et al., 2021), and differential access to providers and vaccines, varying levels of information, and logistic barriers to vaccination faced by different populations (Kim et al., 2022). Second, the clinical trials do not capture changes in behavior following vaccination, such as increased social interactions due to perceived immunity (Trogen and Caplan, 2021), The placebo-controlled and double-blind design of these trials prevents participants knowing of their vaccination status. While in the real world, individuals know theirs and others' vaccination status and may alter their behavior accordingly. These post-vaccination behaviors, often associated with higher risks of infection, could downwardly bias the vaccine effectiveness in observational studies. Third, the emergence of new variants, each with varying capabilities of evading immunity (Cele et al., 2022), further complicates the application of trial results over time. Lastly, it is important to note experiments do not examine some relevant outcomes pertaining to children's overall wellbeing. For instances, mental health, long-term COVID-related symptoms or conditions, and educational and developmental outcomes, which could all benefit from the protective roles of vaccines.

Extant Studies on the Protective Effects of Vaccines in the Real-World Setting

While the limitations of clinical trials highlight the need for real-world data, there remains a substantial gap in our understanding of vaccine effectiveness beyond controlled settings. Among a growing body of literature, group-level observational studies and mathematical or simulation models indicate that vaccination confers collective protection against infections, hospitalizations, intensive care unit (ICU) admissions, and deaths (Moghadas et al., 2021; Suthar et al., 2022). Similarly, individual-level observational studies, including meta-analyses, corroborate the substantial protective outcomes across diverse contexts and against multiple viral variants (Britton et al., 2022; Corchado-Garcia et al., 2021; Feikin et al., 2022; Ssentongo et al., 2022). Specifically, these studies find similar estimates in vaccine efficacy among different COVID-19 vaccines, with protective rates against infection ranging from 40% to over 90% – sometimes lower than for severe outcomes such as hospitalization, ICU utilization, and death, where efficacy consistently exceeds 80%. The results are similar based on studies focusing on children and adolescents only (Cohen-Stavi et al., 2022; Fleming-Dutra et al., 2022; Olson et al., 2022; Tan et al., 2022). Notably, the protection effects decrease over time (Feikin et al., 2022), with an average decrease of 20-30 percent over 6 month periods after vaccination.

While most extant studies center on physical health outcomes, a growing trend of studies examined the effects of vaccines on behavioral or mental health outcomes. (Koltai et al., 2022) finds that vaccination was associated with declines in distress and perceived risks of COVID illness based on survey data. Using the Household Pulse Survey, (Agrawal et al., 2021) found improvement in anxiety and depression symptoms following the vaccine release for certain age groups. No studies so far examined mental health outcomes using administrative data, which represents an area for further inquiry.

Despite the highly diverse data sources and methodologies, the consensus is clear: vaccines offer substantial protection in various real-world settings. However, few studies adequately address the potential self-selection bias in vaccine uptake. The self-selection into vaccinations in observational studies will likely lead to an overestimation of vaccine effectiveness, attributable to the generally higher socio-economic status (SES) and pandemic cautiousness of the vaccinated individuals. As such, accurately estimating the effects of vaccines in a real-world setting requires thoughtful applications of the appropriate research methodology. Moreover, the literature falls short in examining the effects of vaccines on children in the context of school, particularly over the course of a school year. This thread of research is crucial since schools represents a primary social and learning environment for children, even more so for low-income families relying on school resources. Also, the frequent interactions and close contact among students pose unique implications for the spread of the virus. Understanding vaccine effectiveness in this context is essential for informing public health strategies aimed at ensuring the continuity of education and the well-being of children in the post-pandemic era. Finally, the literature should examine a broader set of health outcomes that are important to understand the long-term impact of COVID infection (Leung et al., 2020).

Vaccines and Educational Outcomes

Besides health benefits, vaccines also hold the potential to influence educational outcomes. While there are no published studies directly linking vaccines to educational outcomes among children, the potential mechanisms make this worth exploring. The pandemic significantly impacted education and schooling, with varying effects over time. In the pandemic's early stages, disruptions arose from school closures and pedagogical changes suboptimal for learning, leading to mental and physical health concerns among students (Alves et al., 2021; Khubchandani et al., 2021; Hoofman and Secord, 2021; Van Lancker and Parolin, 2020). These impacts extended to the loss of socialization and normal activities crucial for learning, especially among younger children. In the later phases of the pandemic, with students returning to in-person learning, vaccines could mitigate the disruption of education by reducing illnesses, including COVID infection or related illnesses, which could lead to absenteeism and learning loss (Nathwani et al., 2021). The vaccine is particularly beneficial in a population-dense area or settings with prolonged indoor activities, e.g., schools and care centers (Chernozhukov et al., 2021). Given the well-established connection between one's health and education (Eide and Showalter, 2011), vaccines could also reduce the risks of health conditions from impeding learning in the long run, such as cardiovascular and endocrine-related diseases (Kompaniyets et al., 2022; Shaw et al., 2015; Chomitz et al., 2009). Furthermore, vaccines might reduce perceived health risks and mental health concerns, thus encouraging participation in social events and activities conducive to learning (Tandon et al., 2021; Stephenson, 2021).

Currently, only one study has rigorously examined the causal effects of vaccines on children's health outcomes within a school environment (Freedman et al., 2022). Utilizing federal age-based vaccine eligibility criteria as a natural experiment, the authors compared students who became eligible earlier with those who did later. They discovered that the direct effects of vaccines have a similar effectiveness in preventing COVID infection to that of clinical trials. Furthermore, they explored the indirect effects of vaccines on unvaccinated, age-ineligible students. Their findings indicated minimal indirect benefits, particularly when comparing students in stand-alone elementary schools to those in mixed-age educational settings. Building upon this foundation, this study extends the scope of investigation to include educational outcomes alongside a more comprehensive set of health outcomes, utilizing Medicaid claims data. I aim to not only assess the immediate impact of vaccines but also their longitudinal effects. While the primary focus of the study remains on the direct effects of vaccines, I also include the analysis of indirect effects in the appendix.

Data and Research Design

The Student Population Health Registry (SPHR)

The study utilizes a comprehensive student data registry, namely the Student Population Health Registry (SPHR), which aims to link multiple administrative data sources for public school students in New York City. Under a collaboration between New York University, NYC Department of Health and Mental Hygiene (DOHMH), and the Department of Education, the registry links student enrollment files and educational records from all NYC public schools to immunization information, as well as comprehensive health records for students enrolled in Medicaid. Specifically, the enrollment data includes the student's name, Social Security Number (SSN), date of birth, gender, grade, race and ethnicity (reported by parents or guardian), whether an English Language Learner (ELL), their residential address, and the school the student attended. The educational records include data on absences reported weekly and standardized test scores for students in grades 3-8. For the purpose of this study, the educational data includes the universe of public and charter school students in NYC, which makes up around 80% of all children in NYC (U.S. Census Bureau, 2021).

The immunization history is provided by the City-wide Immunization Registry (CIR), a database accessed through DOHMH that keeps the records of all vaccines administered to children in NYC, or elsewhere if relevant documents were uploaded. The vaccine records include information on the type, dosage of vaccines, date and location of administration, and the vaccine-ordering provider. These records are linked to the student data via an internal student identifier created by the agency for vaccine compliance and public health surveillance purposes.

Additionally, to link the educational records of students to their Medicaid claims, I probabilistically matched them based on information available from both their enrollment. The shared information used to perform the match include student name, date of birth, SSN, gender, race and ethnicity, residential zip-code. This step completes the data linkage of the registry and allows us to build a longitudinal database for a sample of students enrolled in Medicaid, with their education and health related outcomes linked.

Research Design

This study aims to estimate the impact of COVID-19 vaccines on the health and educational outcomes of NYC public school students. The key identification strategy leverages the quasi-experimental context created by the age cutoff in the vaccine eligibility rule, where the FDA granted vaccine eligibility to students 12 – 15 years old in May 2021, followed by those aged 5 – 11 in November 2021. This policy of sequential vaccine rollout by age groups allowed those otherwise similar students around the 12-year-old cutoff to have a temporary difference in eligibility. Specifically, the treatment group are early eligible students aged 12 – 12.5 as of May and the control or late eligible students are those 11 – 11.5 years old during the same period. In the context described earlier, early eligible students could vaccinate against COVID in May while the late eligible students had to wait until November. Consequently, the vaccination rates in the early eligible group steadily rose since May while the late eligible group remained unvaccinated until November. Given how closely aged these two groups are, I posit that the variations in the vaccine uptake were exogenous, stemming from policy-driven eligibility rather than individual characteristics or prior outcomes. Therefore I utilized this early eligibility status as an instrumental variable to estimate the effects of vaccination decision on student health and education outcomes within two distinct analytical frameworks, which are delineated in the ensuing sections.

End-of-School-Year Analysis

In this section of analysis, I employ an IV framework, where I use the early eligibility status as an instrument for student vaccination decision. This framework allows us to estimate the reduced-form effects, or Intention-to-Treat (ITT) of early eligibility and Local Average Treatment Effects (LATE) of vaccine uptake on health and educational outcomes in the 2021-2022 school year. I estimate with equations (1) and (2) using the cross-sectional variation of the data. This is because some educational outcomes, such as test scores and chronic absenteeism, are only available as a final tally by the end of school year. Moreover, the standardized tests first resumed with full in-person instruction in the 2021-2022 school year since the pandemic, so prior test scores after 2019 are not available due to the disruption of the pandemic. To provide comparable estimates of the effects of vaccines on health outcomes, I estimate aggregated total counts of visits or diagnoses throughout the school year (so that the date of service falling in between September 2021 to July 2022).

A critical consideration in this framework how to measure vaccination status in the study period using cross-sectional data. Rather than relying on a binary indicator denoting vaccination at a specific point in time, I construct several measures to reflect the duration of being fully vaccinated. These measures include whether individuals were fully vaccinated before the commencement of the school year (either by the first day, 9/13/2021, or by the end of the first month, 10/2021) and the number or percent of school days spent while fully vaccinated. For ease of interpretation, I scale the reduced-form estimates by the percentage increase in days while fully vaccinated to derive the LATE estimates. The coefficient β_{LATE} represents the effect of an additional 50% of the school days spent vaccinated compared to none. When this magnitude is doubled, it reflects the differential impact of full vaccination throughout the school year versus no vaccination. Although the binary measure of vaccination before the first day or month is straightforward, it may lead to mis-specification by not accounting for similar duration of protection among those vaccinated shortly after the school year begins. Results using other vaccination measures are provided in the appendix.

Reduced form (ITT) model:

$$Y_i = \alpha + \beta Z_i + \omega X_i + \epsilon_i, \tag{1}$$

where Y_i are the educational outcomes reported at the end of school and health outcomes aggregated throughout the school year, Z_i is the early eligibility status, X_i is a matrix of student-level and neighborhood-level characteristics. The coefficient β represents the estimated effects of early eligibility on the outcomes, i.e., Intention-to-Treat (ITT).

Two-stage-least-squares (2SLS) model:

$$\begin{aligned} \text{First Stage:} \quad & D_i = \alpha' + \pi Z_i + \omega' X_i + \nu_i \\ \text{Second Stage:} \quad & Y_i = \alpha + \beta_{\text{LATE}} \hat{D}_i + \theta X_i + \epsilon_i, \end{aligned} \tag{2}$$

D_i is the vaccination status, and I use the early eligibility Z_i as an instrument for the vaccination status to derive the estimate of the Local Average Treatment Effects (LATE).

The identifying assumptions for β_{LATE} follow those of the standard assumptions of an IV framework. I conduct the following analysis to assess the validity of this analytical framework. First, I demonstrate the relevance of the instrument by estimating the impact of early eligibility on various measures of vaccine uptake across multiple model specifications and report their robust F-statistics (Olea and Pflueger, 2013) of the first stage regression model. Second, to support the independence and exclusion assumption, I conduct a series of balance and placebo tests. These tests compare the student demographics, neighborhood characteristics, and egocentric measures between the early and late egibile students. To rule out that the distribution of these characteristics or outcomes could vary over student age within each group, I employ non-parametric methods (Cattaneo et al., 2019), namely bin-scatter plots, to visually inspect and compare the conditional distributions of these characteristics. Moreover, I compare the health outcomes of these students before vaccine was released to make sure there were no pre-existing differences or differential trends between the groups. Lastly, I compare the tests scores available to us before the pandemic to show that the outcome of these two groups will not be statistically different in the absence of the treatment.

During-School-Year Analysis

In this framework, I estimate the effects of early eligibility and vaccine uptake on health outcomes with a balanced student-month panel. To start, I estimate a standard event study model as follows.

Event study model:

$$Y_{it} = \alpha + \sum_{-4,}^{0} \beta_{pre,t} Z_i \times \text{Month}_t + \sum_{0}^{14} \beta_{post,t} Z_i \times \text{Month}_t + \gamma_t \text{Month}_t + \theta X_i + \epsilon_{it}, \tag{3}$$

This model specification allows us to estimate the relative difference in outcomes between the early and late eligible students over time, both before and after the release of vaccines in May. There are 19 calendar months in total, with Jan. 2021 to May 2021 serving as the pre-vaccine release period and June 2021 to July 2022 as the post-vaccine period. The pre-period coefficients also serve as a preliminary statistical test of the balance of pre-trends in outcomes, which will support the parallel trends assumption if none are statistically significant. Provided in the appendix, I conduct power analysis for the event study results following (Roth, 2022).

In addition to the event study, I estimate Intent-to-Treat (ITT) of early eligibility and Local Average Treatment Effect (LATE) of vaccine uptake within an Instrumental Variable Difference-in-Differences (IV-DID) framework, rendering weighted-average effects for the entire post-period. Specifically, the model specification is as follows. I estimate the ITT on health outcomes using equation (4) and the LATE on health outcomes using equation (5) . The vaccination status and health outcomes in equation (3 - 5) are all binary indicators for the ease of interpretation. Results using total counts of the outcomes can be found in the appendix. Robust standard errors clustered by census tract are estimated in all the models above.

Reduced form effects with Difference-in-Differences model:

$$Y_{it} = \alpha + \beta_{\text{DID}} Z_i \times \text{Post}_t + \gamma Z_i + \delta \text{Post}_t + \theta X_{it} + \epsilon_{it} \tag{4}$$

Two-stage-least-squares (2SLS) model:

$$\begin{aligned} \text{First Stage:} \quad & D_{it} = \alpha' + \pi Z_i \times \text{Post}_t + \gamma' Z_i + \delta' \text{Post}_t + \theta' X_{it} + \nu_{it} \\ \text{Second Stage:} \quad & Y_{it} = \alpha + \gamma Z_{it} + \delta \text{Post}_t + \beta_{\text{LATE}} \hat{D}_{it} + \theta X_{it} + \epsilon_{it} \end{aligned} \tag{5}$$

The primary identifying assumption for the ITT is the assumption of parallel trends between the early and late eligible students. For LATE, the assumptions include the random assignment of early eligibility and that early eligibility affects the outcomes only through an individual's decision to vaccinate. Additional assumptions regarding the estimates of these models include that no external interventions or events that could differentially influence the health outcomes of children at different ages, and no spillover effects where one student's vaccination decision affects other student' decision or outcomes. While these assumptions are not directly testable, I provide a wide range of balance checks and placebo tests that will support the feasibility of these assumptions. However, it is obvious that there will be spillover effects because of the indirect effects of vaccines – the protective effects of being around those who are vaccinated and therefore reduced likelihood of infection for all students. Thus, the estimated the effects (β_{DID} and δ_{LATE}) could be a combination of both direct (on own outcomes) and indirect effects, which actually reflect the overall protective effects of vaccine uptake in light of interactions between the vaccinated and unvaccinated. Following (Freedman et al., 2022), I estimate the cross-grade indirect effects of the vaccines, with which I can assess the magnitude of direct effects in relation to the main estimates.

Variables and Measurements

The key independent variables is the early eligibility status. Students who were 12 to 12.5 years old when the vaccines were released for the 12-15 age group became eligible early, whereas students of 11 to 11.5 years old had to wait until November to be eligible.

For the end-of-school-year framework, the various measures of vaccine uptake are the outcomes of the first stage regressions. Then for reduced-form and LATE estimates, I evaluate educational and health outcomes aggregated through the course of the 21-22 school year. For educational outcomes, I assess academic performance and school attendance. Specifically, the academic performance is measured by the standardized test scores in math and reading, where scale scores were initially reported and then standardized by grade and year among all test-takers. Additionally, I utilize a binary indicator to denote proficiency in the testing subject, defining proficiency as a reported performance level higher than 2 on a 0 to 4 scale. For attendance outcomes, I measure the total number of absences and employ a binary indicator of chronic absenteeism, defined as missing over 10% of all school days. Considering the ongoing COVID risks, I also created a proxy variable for sick days, defined as medical visits (excluding ED visits which can happen outside the school hours) on a school day, as recorded in Medicaid claims. Both total number of medical visits and a binary variable of any medical visits were assessed.

In this paper, I examine a broader set of health outcomes than most previous studies (Tartof et al., 2023; Freedman et al., 2022), utilizing Medicaid data. These outcomes can be categorized into COVID vaccination status, healthcare usage, COVID-related outcomes and post-COVID conditions. The vaccination status refers to if the student is fully vaccinated against COVID. In the end-of-school-year framework, I utilize several measures of the duration of vaccination protection as both the outcomes of the first stage and the endogenous variable in the IV framework. In the during-school-year framework, the vaccination status takes a binary form and is measured on a student-month level.

Healthcare usage includes the separate examination of outpatient, Emergency Department (ED) visits and hospitalizations for any reason or diagnosis. COVID-related illness is assessed by examining any visits with a primary diagnosis of COVID infection , COVID-related outpatient and ED visits, as defined by a recent study (Tartof et al., 2023). The COVID-related visits are defined as outpatient or ED visits with a primary diagnosis that indicates a concurrent potential COVID infection, such as COVID infection or symptoms suggesting a COVID infection. The detailed list of these diagnosis codes is included in the appendix. For these outcomes, I calculate both the total count and a binary indicator of usage.

Moreover, to assess the long-term risks of certain conditions among children following a COVID infection, I look at a series of post-COVID conditions that usually occurred approximately 4 weeks after the onset of COVID infection. The list of conditions under examination is based on recent data (Kompaniyets et al., 2022) among children from the Center for Disease Control and Prevention (CDC) and is included in the appendix table A 1.1. For each condition, I assess both the total number of diagnoses and the presence of any diagnosis.

In the during-school-year analysis, I utilize the vaccination status and all health outcomes as binary indicators. This way, the vaccination status measures whether a student is fully vaccinated and the health outcomes indicate whether the student had a certain visit or diagnosis in that month. The decision simplies the interpretation of the results because for most outcomes the frequency of occurrence is fairly low on a student-month level.

The control variables include student demographic variables such as gender, if an English learner, race and ethnicity, and borough of residence. Additionally, I incorporate neighborhood-level characteristics from the American Community Survey 5-year estimates data, including median income, total population, share of all residents with health insurance, and the average number of bedrooms. Some other variables used in the analysis include distance between the student home to the nearest official vaccine site (location provided by DOHMH) and neighborhood level (ZIP-code) total COVID positive rates published by DOHMH. The proximity to the nearest vaccination site is a proxy for access to COVID vaccines.

Additional Analysis

Recognizing the disproportionate impact of the pandemic across race and ethnicity groups and borough lines, I examine the potential heterogeneous effects of early eligibility and vaccine uptake separately across these subgroups. Similarly, I partition the analysis by quartiles of ZIP-code-level cumulative COVID-19 positive rates, a direct measure of severity of the infection by geography. Moreover, I stratify the analysis by gender and English learner status, which are characteristics that reveal differential vaccine uptake in previous studies. For the consistency of estimates across health and educational outcomes, all main analysis use the sample of students who are enrolled in Medicaid in the analytical sample. Results with all students and non-Medicaid students on educational outcomes will be provided in the appendix. Post-COVID conditions encompass a range of specific conditions. To deepen our understanding, I aim to categorize these based on the affected human systems. This stratification will help us discern any potential heterogeneity associated with the main estimates. These results will be included in the appendix.

Though the main analyses of the study- focus on the direct effects of vaccination (for own outcomes), the estimates inevitably would incorporate any potential indirect effects of the vaccine, i.e., reduced probability of infection due to high peer vaccination rates. It is important to distinguish these effects, though empirically the indirect effects most likely will downwardly bias the reduced-form results if not isolated while estimating. This is because the control students could benefit from the protective effects for being around vaccinated peers. To assess the magnitude of the indirect effects, I compare late eligible students who go to a middle-high school to those in a mix-grade school , where the peer vaccination rates vary substantially because of the age of their peers. In other words, the indirect effects are estimated by comparing late eligible students whose peers have higher vaccination rates to those whose peers have lower. Another potentially moderating factors relates to the physical environment of the classroom, i.e., class size, which may affect the transmission of COVID-19. I examine the role of this variable in the secondary analysis included in the appendix.

In addition to the placebo tests on the instrument validity, I conduct the following robustness analyses. First, I want to check if the results are sensitive to model specification, variable definition, or the clustering level of the standard errors. Second, to assess the possibility that the observed estimates are simply temporal fluctuations unrelated to vaccine deployment, I conduct a falsification test by randomly assigning vaccine release months and replicating the analysis. Lastly, considering that the treatment group is marginally older, hence more likely to be in a higher grade, I control for potential confounding by grade-level differences; I transform the educational outcomes to the percentile rank of test scores within each respective grade which accounts for ages differences and only compares students with peers in the same grade. I also assess the influence of school type to ensure that observed outcome disparities are not artifacts of differing student compositions or school sizes between middle and mixed-grade schools.

Results

Quasi-experiment and vaccine uptake

The universal age-based eligibility rule creates a quasi-experiment among those around the age of 12, which induced significant differences in vaccine uptake among otherwise very similar children. The analytical sample includes Medicaid students in public school between the age of 11- 11.5 and 12 to 12.5 as of the vaccine release in May 2021. Table 1, presented below, details the descriptive statistics of the analytical sample, stratified by their early eligibility and vaccination status. With the exception of age—a difference inherently crafted by the definition of early eligibility—all other demographic characteristics of the students remain remarkably consistent across early eligibility status, with their balance further validated by the two-sample t-test. In contrast, aside from gender, these characteristics demonstrate significant and systematic imbalance between the vaccinated and unvaccinated cohorts. In terms of vaccination related measures, those early eligible students have considerably higher vaccine uptake across several different measures, including ever fully vaccinate (63 vs 50 %), ever boosted (5 vs 15 %), and percent of days in a school year while fully vaccinated (56.1 vs 26.6 %). These results together suggest that early eligibility led to significant differences in vaccine uptakes among students of similar age and demographic backgrounds. However, the differences between those ever vaccinated and not suggest apparent self-selections into vaccination.

The trends of full vaccination rates by early eligibility status are shown in figure 1 below. Students began to vaccinate right after becoming eligible in both May (early eligible) and November (late eligible), yet the timing difference led to a considerable difference in vaccine uptake between the two groups. Notably, the gap in vaccine uptake stabilizes to be about 13 percentage points around May 2022, one year after the initial vaccine release, and persists through April 2023. This sustained gap in vaccine uptake is large when the magnitude accounts for 22 % of the overall full vaccination rates observed in the study sample.

End-of-school-year results

The results for the end of the school year are presented in Table 2. In panel (a), the estimated first stage effects of early eligibility suggest a considerable increase in various measures of vaccine uptake. Early eligibility increased the probability of full vaccination before the school year began by 37.4 percentage points. Furthermore, it elevates both the number of days and the percentage of the school year spent in a fully vaccinated state by 83.7 days and 29.2 percentage points, respectively. The probability of ever becoming full vaccinated was increased by 13.1 percentage points.

In panel (b), I report the reduced form and IV estimates for educational outcomes. Early eligibility and vaccine uptake did not influence absences but reduced the number and probability of having medical visits (proxy for sick days) on school day in the 21-22 school year. Early eligibility reduced 0.14 days of medical visits on school days and probability of having any visits by 3.7 percentage points, which represent approximately 10% reductions compared to the overall mean of 1.2 days and 43 percent, respectively. When considering LATE, a 50% extension in the days of a school year spent fully vaccinated decrease the number and probability of medical visits by 0.247 days and 6.7 percentage points respectively. Extrapolating these results to reflect full vaccination throughout the entirety of the school year, I find reductions amounting to 0.479 days (40% decrease) and 12.7 percentage points (30% decrease). For the academic outcomes, early eligibility and vaccine uptake exhibited beneficial effects, particularly more robust in math than reading scores. To be specific, early eligibility increased standardized math scores by 3.7% of a standard deviation and reading scores by 1.5%. The probability of attaining proficiency in both subjects increased by 6.3 and 2.7 percentage points, respectively. In the ensuing discussion, these figures will be benchmarked with prior educational interventions to offer perspective on the magnitude of these effects.

In panel (c), I present the results on the health outcomes aggregated through the 21-22 school year. Early eligibility and vaccine uptake decreased the number of any and COVID-related outpatient visits, COVID-related ED visits, the probability of ever infected with COVID and having any of the post-COVID health conditions but not any ED visits or hospitalization. The ITT decreased these outcomes by about 15- 20 % compared to the overall mean in this period and the vaccine uptake would decrease these outcomes by much more if scaled to vaccinated for 100% of the days in a school year.

During-school-year results

Figure (2) provides a visual representation of the influence of early eligibility on vaccine uptake over time. Subfigure (2.a) illustrates the differences in the probability of full vaccination between early and late eligible students for each calendar month, while (2.b) displays the difference of a cumulative nature in the percentage of days spent fully vaccinated throughout the school year. The point estimates, accompanied by their 95% confidence intervals (indicated by the vertices), are derived from the event study coefficients using equation (3). The disparity in vaccine uptake between the groups widened swiftly in the initial months following the May release. However, this gap contracted and eventually plateaued post-November, aligning with the period when the younger cohort became universally eligible. However, despite this evening out, a persistent and noteworthy disparity in the percentage of days spent fully vaccinated remained across the school year, partly attributable to the additional time of eligibility that the older group got.

Delving deeper, Table 3 sheds light on specific coefficients relating to the first-stage effects across the post-period and on a monthly basis. Leveraging the Difference-in-Differences (DID) framework, the coefficient of the interaction between early eligibility and post illustrates the increase in full vaccine uptake. This manifests as a 24-percentage point increase in uptake, 60.3 additional days, and 21.1% more in the overall days spent in a vaccinated state post-vaccine release. The event study coefficients for each months show the relative difference in various vaccination measures at that time.

In table 4 below, I present the reduced form, IV and event study results using equations (3-5) with the balanced student-month panel. Given the health outcomes are all binary indicators for each student-month observation, the early eligibility decreased the probability of any outpatient visits by 0.7 percentage points, without significantly affecting the ED visits or hospitalizations during the post-period. As for COVID-related outcomes, early eligibility decreased the probability of COVID-infection by 0.1 percentage points, COVID-related outpatient visits by 0.1 percentage points, COVID-related ED visits by 0.03 percentage points, but did not influence post-COVID health conditions. Delving deeper into the LATE of vaccine uptake, the analysis highlights that full vaccination corresponded to a 2.8 percentage point reduction in the likelihood of any outpatient visits, and 0.3 percentage points, 0.1 percentage points for both COVID infection and COVID-related outpatient visits, and COVID-related ED visit respectively. Taken together with the period-mean of the respective outcomes, it becomes evident that the vaccine's efficacy in mitigating these health outcomes is significant during this period. Notably, vaccine uptake reduced COVID infection by 60% and COVID-related ED visits by 100%. Though smaller, the protective effects are still palpable for any outpatient visits and COVID-related outpatient visits, each generating a decrease slightly over 40%.

The event study coefficients denote the relative differences in the outcomes between the early and late eligible groups each month, revealing the potential heterogeneous effects over time. Early eligibility persistently reduced the probability of any outpatient visits from November 2021 to June 2022, which covers the majority of the 21-22 school year. For other outcomes, the significant protective effects mostly concentrated around the months between November and January, a period of the worst wave of COVID infection in NYC due to the initial spread of the Omicron variant (B.1.1.529). Notably, the magnitude of the relative differences during this period are also heightened, suggesting stronger protective effects when facing elevated infection risks. The delay of the protective effects until late fall could be because students were still getting vaccinated, and it requires time to generate herd immunity from a higher group-level vaccination rate. Figure 3 visually represents these results, capturing the trends for both outpatient visits and COVID infection throughout the study. Both subfigures 3.a and 3.b indicate an absence of the statistically different pretrends. While both outcomes experienced significant and relatively large (compared to the post-period mean) decrease due to early eligibility, the effects on any outpatient visit persisted longer than infection, possibly due to additional symptoms or complaints that need to be addressed following higher risks of COVID infection

Results of additional analysis

In Table 5, I explore the heterogeneous effects of early eligibility and vaccine uptake on health outcomes. The outcome of all estimates in table 5 is any outpatient visits since it is the only outcome that has shown consistent heterogenous effects. In Panel A, focusing on the disparities by student race and ethnicity, I observe that the first stage effects of early eligibility reveal notable variations across ethnic groups. Asian students led with a coefficient of 32.7 percentage points, followed by Hispanics at 26 percentage points while Black and White students have lowest first stage effects less than 20 percentage points. The Intention-to-Treat (ITT) effects uniformly show reductions across student race and ethnicity, except for students of other race and ethnicity. Similar to ITT, the LATE results show consistent decreases ranging from 2 to 4 percentage points in probability of having any outpatient visits, with the "White" demographic registering the most significant reduction at 0.047 ($p<0.01$). Taken together with the post-period mean, I calculate the average percent decrease of vaccine uptake on the probability of any outpatient visits, with Black and White students demonstrating the largest effect size around 60%, who happen to be populations having the lowest full vaccination rates.

In Panel B, which categorizes results by borough of residence, each borough exhibits somewhat similar increase in full vaccination rates except for Manhattan and Staten Island reporting a lower first stage effect. In terms of the ITT and LATE, I observe consistent decline across boroughs. However, students in Manhattan and Staten Island experienced a steeper decline of the outpatient visits at over 1 percentage points for ITT and 5 percentage points for LATE. The effects of vaccine uptake in both boroughs translate to remarkable average percent decreases of over 80% relative to the post-period mean. Lastly, Panel C presents results stratified based on quarters of neighborhood (proxied by ZIP-code) cumulative COVID infection rates. The first stage effects are similar across all neighborhoods. However, the ITT and LATE reveal a similar decrease in probability of any outpatient visits across all neighborhoods except the first quarter that had the smallest cumulative positive rates and the effects from vaccine uptake and early eligibility. This result may suggest the protective effects may be less pronounced in neighborhoods of the lowest quartile regarding risk of infection. I have also examined heterogeneity by student gender and English learner status but did not observe any. Together these results reveal the potential heterogeneity of the effects of early eligibility and vaccine uptake on health outcomes across important dimensions that could inform a wide variety of public health and policy responses.

In other additional analyses, I provide more detailed descriptive statistics of the student-level characteristics and their outcome variables in the appendix. Then, I perform the analysis in equation (1-2) with a different sample – non-Medicaid students. Those enrolled in Medicaid exhibit demographic characteristics distinct from their non-enrolled counterparts. Most notably, students with Medicaid tend to reside in tracts with a considerably lower median income compared to those without Medicaid. However, I did not find any significant effects among non-Medicaid students, suggesting the heterogeneity by Medicaid enrollment status. Considering that students with Medicaid constitute approximately 75% of all NYC public school students, results from an all-student sample closely mirror those from the Medicaid-only sample. Moreover, I examine the indirect effects, defined as the benefits of vaccines for being around the vaccinated, which could be part of the main effects I estimated in addition to the direct effects. The indirect effects estimated by comparing late eligible students in mid-high school to those in mix-grades school are small and statistically insignificant, which is similar to the estimate from the previous study (Freedman et al., 2022). This suggest that the direct effects I estimated might not be downwardly biased with this additional channel of effects at play. Lastly, I did not observe class size having any moderating effects in the analysis though higher classroom density may mechanically increase the likelihood of COVID transmission. All results mentioned above can be found in the appendix.

Results of placebo and robustness analyses

First, I conducted a series of placebo test to assess the validity of using the early eligibility as an instrument for vaccine uptake. Specifically, I test the balance of all student and neighborhood level covariates across the early eligibility status. Nearly all covariates achieved the statistical balance, the few that did not have differences less than 1% relative to the mean and are not likely to have any meaningful influences. Then I employ the bin-scatter plot to non-parametrically examine the distributions of these covariates conditional on the relative age within each group. The distributions over relative age are smooth and have good symmetry across the early eligibility status, indicating no evidence of a differential influence over the relative age within each group. In other words, these characteristics do not depend on the relative age within each group. Notably, even if variable distributions trend insignificantly over age, symmetry exists in both early and late eligible groups. This further emphasizes balanced observed characteristics between them. I conducted a similar analysis using health outcomes, confirming that children's health was not influenced by being relatively older or younger. Moreover, none of the pre-trends between the early and late eligible groups are significantly different from each other. This is also true when I extend the length of pre-period to include late 2020. Lastly, I compare the past test scores of the same students who took tests in the 21-22 school year and found no significant differences. This assures that no systematic differences in the test scores existed before introduction of COVID vaccines.

Second, in the additional robustness checks, I assess the sensitivity of the main results in both end-of- and during-school-year analyses. I do this by checking the sensitivity of various model specifications, including the inclusion of student, tract-level characteristics, school, ZIP-code or tract fixed effects. The main results remain consistent with all these specifications. Next, I test the sensitivity of the definition of the early eligibility status. The primary definition compares $12 - 12.5$ years old to $11 - 11.5$ years old. The alternative definition compares students 12-13 years old to 11-12 years old, except that the first stage effects become a bit attenuated. This is because the $11.5 - 12$ years old can age into eligibility before November, therefore becoming eligible sooner than the $11 - 11.5$ years old. All other results using the alternative definition are qualitatively the same as the results using the primary definition, including various balance checks. Lastly, to eliminate the possibility that the results arose by chance, I assigned a random vaccine release month for analysis. Presented in the appendix, the outcomes revealed no significant results with this random post indicator.

Discussion

The COVID-19 pandemic has had a profound influence on society, with a disproportionate impact on less privileged populations, including minority and low-income children. The resulting substantial learning loss and pandemic-related illness may have enduring ramifications. This study offers fresh insights into the protective effects of COVID vaccines on students' health and academic performance within a school environment. By taking advantage of universal age-based vaccine eligibility rules, I addressed potential bias in vaccination decisions. Employing a database that integrates students' educational and health records, the findings indicate that early or extended eligibility substantially boosts vaccine uptake, enhancing the time students spend in school fully vaccinated. Such increase in COVID vaccine uptake translate into improved math test scores, reduced medical visits on school days, outpatient visits and COVID infection. During times of elevated community infection rates, the vaccines' protective effects were most marked, with the protective effects extended to prevent COVID-related ED visits. Given NYC's unique context, the study documents the heterogeneous effects of the vaccine's capability to reduce any outpatient visits by student race and ethnicity, borough of residence and ZIP-code level cumulative infection rate.

This study has several limitations. First, I rely on Medicaid insurance claims to measure COVID infections, which may severely underestimate the prevalence of COVID infections among students a potential issue shared by other types of healthcare data such as Electronic Health Records. Though given the strengths of the study design, this underestimation is not likely to bias the estimates. For the same reason, I cannot study the health outcomes of those who were not enrolled in Medicaid. Second, I can only study those around the age of 12 because of the research design, which limits my ability to generalize the results to older or younger students. Third, the pandemic may have influenced how data was collected and stored during this time. For example, the attendance data provided by DOH received retrospective corrections, which prevented us from examining its variation over time.

The study contributes to the evidence of protective effects of vaccines in a real-world setting. In this study, the real-world data reveals the important implications of vaccine hesitancy. The estimation of ITT illustrates the potential effect size on a population level where the proportion of never-takers may vary. Such results can also inform the policies regarding vaccine promotion and pandemic mitigations. The revealed heterogeneities regarding the differential vaccines uptakes and LATE can also inform more contextualized and targeted policies. These findings again highlight the importance of real-world data.

The integrated educational and health records enabled us to confirm the vaccines' protective effects on students' educational outcomes, suggesting another dimension to the known benefits of vaccination: fostering cognitive development and human capital accumulation in children. For instance, early eligibility enhanced math test scores by 3.7% of a standard deviation, with effects for full school year vaccination being 12% of a standard deviation. The size of these effects are substantial, especially compared to other interventions, such as the summer school and grade retention in Chicago (Hoofman and Secord, 2021) and the income transfer from the Earn Income Tax Credit (EITC) program (Dahl and Lochner, 2012). The beneficial effects of vaccines on academic performance are more consistent on math than reading. I speculate this could be because the pandemic impacts math more than reading (Kuhfeld et al., 2020), so vaccinated students had less interruption due to sickness and perhaps felt more confident in partaking in-person learning and other activities. Another related reason might be the accumulation of math is more sequential and therefore more prone to disruptions, e.g., missing a class due to illness. Besides, the strong evidence on the protective effects of vaccines on health may also boosted education performances, for example, vaccinated students experienced over 60% reduction in COVID infection, and around 40% for outpatient and COVID-related outpatients, and almost prevented all COVID-related ED-visits.

Considering the findings, COVID vaccines might be linked to a broader spectrum of outcomes, such as human capital accumulation (Miller and Wherry, 2019) and long-term effects rooted in early childhood experiences (Goodman-Bacon, 2021). While I anticipated enhancements in mental health outcomes, the Medicaid data didn't reflect this. One paper using survey data found encouraging results of vaccines on mental health outcomes (Koltai et al., 2022), suggesting that Medicaid data is not the best measure of mental health-related symptoms, especially among children.

The study results offer several policy considerations. First, the reduced medical visits and loss of learning could generate substantial cost savings, especially on a population level. Second, the vaccine distribution strategy should factor in the equitable distribution for children around the eligibility cutoff. I found a 13-percentage points gap (over 20% relative to the overall vaccination rate) in the probability of full vaccination between the early and late eligible group two year after the initial vaccine release. Such unintended consequences of policy may result in long-term disparity in risks of COVID-related illness. Lastly, the study's insights could shape future public health strategies, especially if COVID evolves into a seasonal virus, akin to influenza and Respiratory Syncytial Virus (RSV).

Tables and figures

Table 1

Table 1: Descriptive Statistics of Student Characteristics by Early Eligibility and Vaccination Status

	Eligibility		Fully Vaccinated		Overall
	$Z_i = 0$	$Z_i = 1$	$D_i = 0$	$D_i = 1$	
Age (as of release date)	11.25*	12.25*	11.68*	11.82*	11.76
	(0.15)	(0.14)	(0.52)	(0.51)	(0.52)
Male	0.51	0.51	0.52*	0.51*	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
English learner	0.31*	0.32*	0.26*	0.36*	0.32
	(0.46)	(0.47)	(0.44)	(0.48)	(0.46)
Race or Ethnicity					
Asian	0.16	0.16	0.07*	0.22*	0.16
	(0.36)	(0.36)	(0.25)	(0.42)	(0.36)
Black	0.27	0.27	0.33*	0.22*	0.27
	(0.44)	(0.44)	(0.47)	(0.41)	(0.44)
Hispanic	0.47	0.47	0.45*	0.48*	0.47
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Other	0.02	0.02	0.02*	0.02*	0.02
	(0.15)	(0.14)	(0.15)	(0.15)	(0.15)
White	0.08	0.09	0.13*	0.05*	0.09
	(0.28)	(0.28)	(0.33)	(0.23)	(0.28)
Borough of Residence					
Bronx	0.27	0.27	0.29*	0.26*	0.27
	(0.44)	(0.44)	(0.45)	(0.44)	(0.44)
Brooklyn	0.31	0.30	0.33*	0.29*	0.31
	(0.46)	(0.46)	(0.47)	(0.45)	(0.46)
Manhattan	0.09	0.09	0.09*	0.10*	0.09
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
Queens	0.28	0.28	0.23*	0.31*	0.28
	(0.45)	(0.45)	(0.42)	(0.46)	(0.45)
Staten Island	0.05	0.05	0.05*	0.05*	0.05
	(0.22)	(0.22)	(0.23)	(0.22)	(0.23)
COVID vaccine related measures					
Distance to nearest vaccine site	389.05*	388.68*	403.38*	377.90*	388.87
	(276.69)	(279.13)	(290.17)	(267.71)	(277.88)
Ever fully vaccinated	0.50*	0.63*	-	1.00	0.57
	(0.50)	(0.48)	-	-	(0.50)
Ever boosted	0.05*	0.15*	-	0.17	0.10
	(0.22)	(0.35)	-	(0.38)	(0.30)
During the 21-22 school year: fully vaccinated					
in the first month	0	0.47*	-	0.42	0.24
	-	(0.50)	-	(0.49)	(0.43)
before the first day	0	0.38*	-	0.34	0.19
	-	(0.49)	-	(0.47)	(0.39)
for percentage of total days	26.58*	56.09*	-	73.11	41.64
	(29.38)	(46.02)	-	(26.85)	(41.48)
for days	76.28*	160.97*	-	209.82	119.50
	(84.31)	(132.06)	-	(77.05)	(119.05)
Observations	26,735	27,803	23,817	30,721	54,538

Figure 1

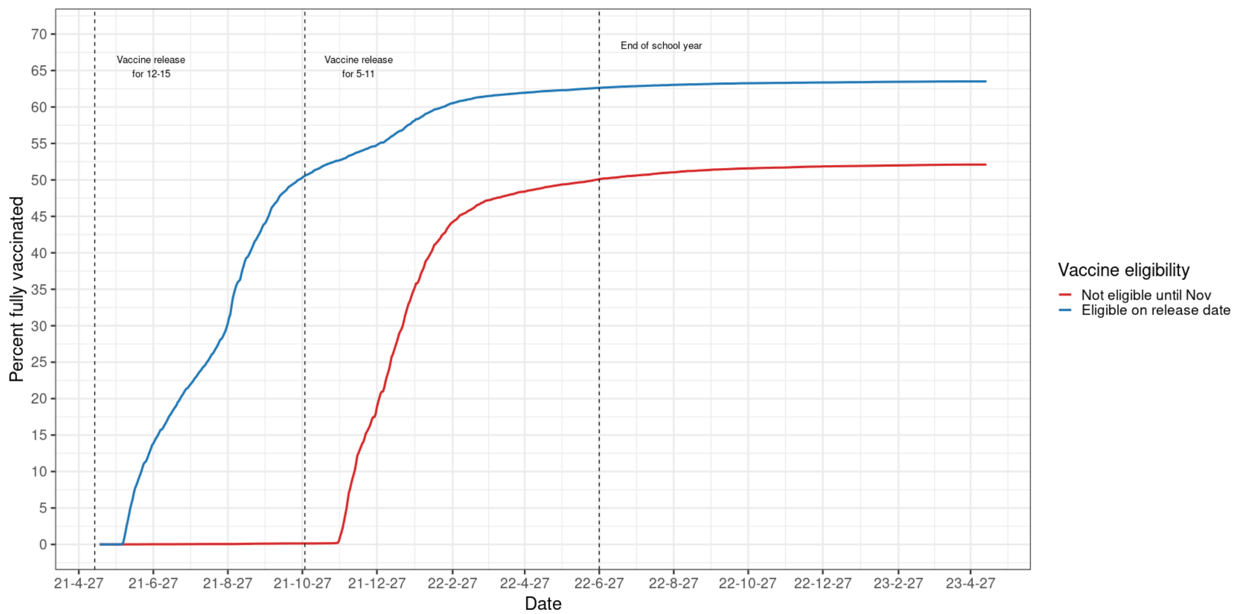


Figure 1: Trends in Percent of Fully Vaccinated by Early Eligibility Status

Table 2

Table 2: Cross-sectional analysis of vaccine eligibility and uptake on educational & health outcomes

((a)) First stage: the effects of early eligibility on full vaccination

	Dependent variable:			
	Vaccinate before the 1st day of school	Num. of days in school while fully vaccinated	Percent of days while fully vaccinated	Ever fully vaccinated
Early eligibility	0.374***	83.653***	29.147***	0.131***
	(0.009)	(1.300)	(0.453)	(0.004)
N (Students)	54,538	54,538	54,538	54,538

((b)) Effects of early eligibility and vaccine uptake on absences and standardized test scores

	Absence-related outcomes:			
	Absences	Chronic absenteeism	Medical visits on school days	Had medical visits on school days
Intention-to-Treat	−0.022	0.002	−0.144***	−0.037***
	(0.117)	(0.003)	(0.023)	(0.004)
Local Average Treatment Effects:				
Vaccinate for 50% of days	−0.038	0.003	−0.247***	−0.064***
	(0.199)	(0.006)	(0.040)	(0.007)
N (Students)	53,150	53,150	53,150	53,150
	Test scores:			
Intention-to-Treat	Standardized reading	Standardized math	Proficient in reading	Proficient in math
	0.015*	0.037***	0.063***	0.027***
	(0.008)	(0.009)	(0.004)	(0.005)
Local Average Treatment Effects:				
Vaccinate for 50% of days	0.025*	0.062***	0.092***	0.038***
	(0.014)	(0.014)	(0.006)	(0.008)
N (Students)	48,542	45,650	48,542	45,650

((c)) Effects of early eligibility and vaccine uptake on health outcomes

	Early eligibility	Vaccine uptake	
Dependent variables:	Intention-to-treat	LATE (per 50 % days)	Overall mean
Outpatient visits	−0.148***	−0.253***	1.28
	(0.019)	(0.033)	
COVID-related outpatient visits	−0.020***	−0.035***	0.11
	(0.004)	(0.006)	
Ever COVID infection	−0.014***	−0.024***	0.07
	(0.0023)	(0.004)	
ED visits	−0.005	−0.008	0.13
	(0.005)	(0.008)	
COVID-related ED visits	−0.005***	−0.008***	0.02
	(0.001)	(0.002)	
Hospitalizations	−0.009	−0.016	0.04
	(0.009)	(0.015)	
Any post-COVID health condition	−0.009**	−0.015**	0.12
	(0.002)	(0.005)	
N (Students)	54,538	54,538	

Note: The coefficients above are based on equation (1) and (2), with robust standard errors clustered by census tract in the parenthesis. Total observations may vary due to availability of certain outcome data. All outcome variables (including means) were measured for the entire 21-22 school year (9/21-6/22). Absence counts and test scores are the final measure of the school year. Chronic absenteeism indicates missing more than 10% of school days. Test scores were standardized based on grade and year. The health-related outcomes are sourced from New York State (NYS) Medicaid, with detailed definitions and relevant diagnosis codes provided in the appendix. The independent variable in the LATE estimates is per 50% increase in total days in a school year while fully vaccinated. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3

Table 3: First stage: the effects of early eligibility on vaccination takeup

	Dependent variable:		
	Full vaccination	Days while fully vaccinated	% of days fully vaccinated
	(1)	(2)	(3)
Difference-in-differences model			
Early eligibility X post	0.240***	60.297***	0.211***
	(0.003)	(0.704)	(0.002)
Post-period event study model			
June 2021	0.115***	3.443***	0.012***
	(0.002)	(0.072)	(0.0003)
July 2021	0.197***	9.356***	0.033***
	(0.004)	(0.172)	(0.001)
Aug. 2021	0.312***	18.712***	0.065***
	(0.005)	(0.302)	(0.001)
Sep. 2021	0.435***	31.756***	0.111***
	(0.005)	(0.444)	(0.002)
Oct. 2021	0.491***	46.503***	0.163***
	(0.005)	(0.583)	(0.002)
Nov. 2021	0.498***	61.445***	0.215***
	(0.005)	(0.717)	(0.003)
Dec. 2021	0.367***	72.455***	0.253***
	(0.004)	(0.810)	(0.003)
Jan. 2022	0.243***	79.746***	0.279***
	(0.004)	(0.881)	(0.003)
Feb. 2022	0.184***	85.276***	0.298***
	(0.004)	(0.954)	(0.003)
March 2022	0.162***	90.146***	0.315***
	(0.004)	(1.036)	(0.004)
April 2022	0.155***	94.799***	0.331***
	(0.004)	(1.125)	(0.004)
May 2022	0.149***	99.266***	0.347***
	(0.004)	(1.222)	(0.004)
June 2022	0.145***	103.606***	0.362***
	(0.004)	(1.324)	(0.005)
July 2022	0.142***	107.858***	0.377***
	(0.004)	(1.430)	(0.005)
N (Students X months)	1,036,222	1,036,222	1,036,222
N (Students)	54,538	54,538	54,538

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Figure 2

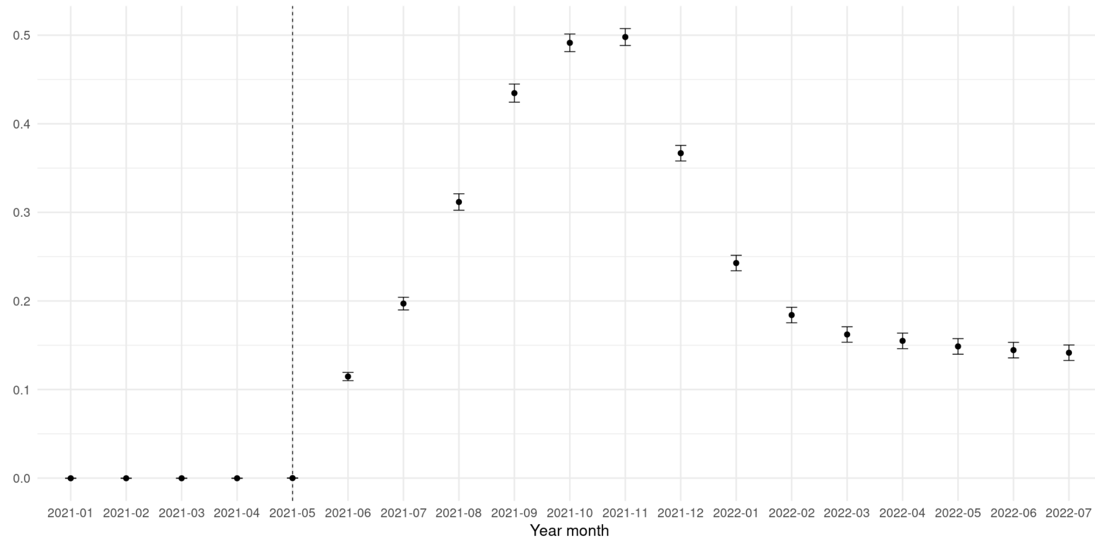


Figure 2.a : The Effects of Early Eligibility on Becoming Fully Vaccinated Over Time

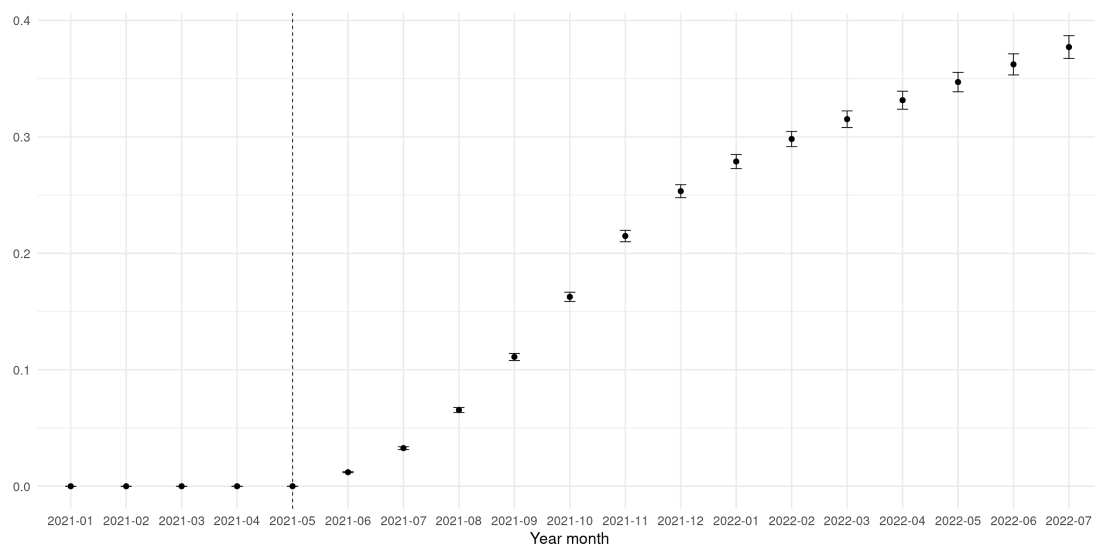


Figure 2.b : The Effects of Early Eligibility on Percent of Days in a School Year While Fully Vaccinated Over Time

Note: The figures show the monthly coefficients from the event study model (3). The outcomes denote the probability of being fully vaccinated (2.a) or percent of days in a school year while fully vaccinated (2.b). The black circle indicates the relative difference in outcomes between the early and late eligibility group, accompanied by its 95% confidence interval. The vertical dotted line refers to the vaccine release date for the 12-15 age group. No difference in the vaccination status was observed before vaccines were released in May.

Table 4

Table 4: The effects of early eligibility and vaccine uptake on various health outcomes

	Indicators of health outcomes:						
	Outpatient visit	COVID infection	COVID-related outpatient visit	ED visit	COVID-related ED visit	Hospitalized	Post-COVID health conditions
Difference-in-differences model							
Intention-to-Treat	-0.007^{***}	-0.001^{**}	-0.001^{*}	0.00002	-0.0003^{**}	0.00003	-0.0003
	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0002)	(0.001)
LATE of vaccine uptake	-0.028^{***}	-0.003^{**}	-0.003^{*}	0.0001	-0.001^{**}	0.0001	-0.001
	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)
Post-period mean	0.07	0.005	0.007	0.008	0.001	0.001	0.024
Percent decrease	40 %	60 %	42.9 %	1.25 %	100 %	10%	4.2 %
Post-period event study coefficients							
June 2021	-0.001^{*}	-0.0005	-0.0002	-0.0005	0.00001	-0.0005	0.002
	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.001)
July 2021	-0.0001	-0.001	-0.001	-0.001^{*}	-0.00004	-0.001^{*}	0.001
	(0.0004)	(0.0005)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.001)
Aug. 2021	-0.0001	-0.001^{*}	-0.001	-0.001^{**}	0.0002	-0.001^{**}	0.001
	(0.0005)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.001)
Sep. 2021	0.0002	-0.001^{*}	-0.002^{**}	-0.0004	-0.0001	-0.0004	-0.002
	(0.0005)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.002)
Oct. 2021	-0.0002	-0.001	-0.002^{*}	-0.0003	-0.0001	-0.0003	-0.0002
	(0.0005)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.002)
Nov. 2021	-0.022^{***}	-0.001^{**}	-0.002^{**}	-0.0001	-0.0002	-0.0001	-0.001
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.002)
Dec. 2021	-0.032^{***}	-0.006^{***}	-0.005^{***}	-0.0005	-0.0004	-0.0005	-0.005^{***}
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.0004)	(0.002)
Jan. 2022	-0.017^{***}	-0.003^{**}	-0.002	-0.001	-0.001^{**}	-0.001	-0.001
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.002)
Feb. 2022	-0.009^{***}	-0.001	0.0001	-0.001^{*}	-0.0002	-0.001^{*}	-0.0001
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.001)
March 2022	-0.006^{**}	-0.001	-0.001	-0.0003	-0.0003	-0.0003	0.002
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.002)
April 2022	-0.007^{***}	-0.001	-0.002^{**}	-0.0002	-0.001^{*}	-0.0002	0.00004
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0004)	(0.002)
May 2022	-0.009^{***}	-0.001^{*}	-0.001	-0.0003	-0.0001	-0.0003	0.0004
	(0.003)	(0.001)	(0.001)	(0.0005)	(0.0004)	(0.0005)	(0.002)
June 2022	-0.007^{***}	-0.0001	-0.001	-0.0005	-0.0004	-0.0005	0.002
	(0.003)	(0.001)	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.002)
July 2022	-0.0005	-0.0001	0.00002	-0.0004	0.00002	-0.0004	0.003^{***}
	(0.001)	(0.0004)	(0.001)	(0.0003)	(0.0002)	(0.0003)	(0.001)
N (Students X months)	1,036,222	1,036,222	1,036,222	1,036,222	1,036,222	1,036,222	1,036,222
N (Students)	54,538	54,538	54,538	54,538	54,538	54,538	54,538

Note: The table presents both the coefficients of Intention-to-Treat (ITT) of early eligibility and Local Average Treatment Effect (LATE) of vaccine uptake on various health outcomes for the study duration (January 2021 to July 2022). Following these are the monthly coefficients from event studies for the post-period (June 2021 to July 2022), using May 2021 as the reference. Standard errors are robust and clustered by census tract. The analysis was conducted on the student-month level following equation (3), (4), and (5), with the student sample consistent with prior analyses. The outcome variables, derived from NYS Medicaid, indicate whether a specific health event or diagnosis occurred in that given month. Detailed definitions and relevant diagnosis codes provided in the appendix. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Figure 3

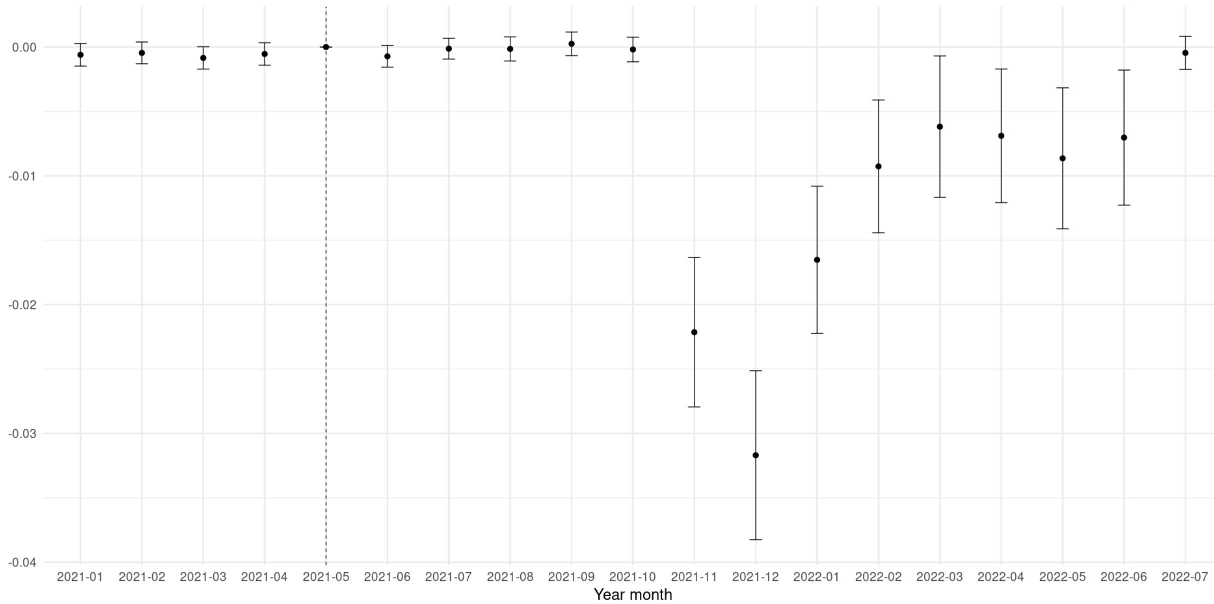


Figure 3.a : The Effects of Early Eligibility on Having Any Outpatient Visit Over Time

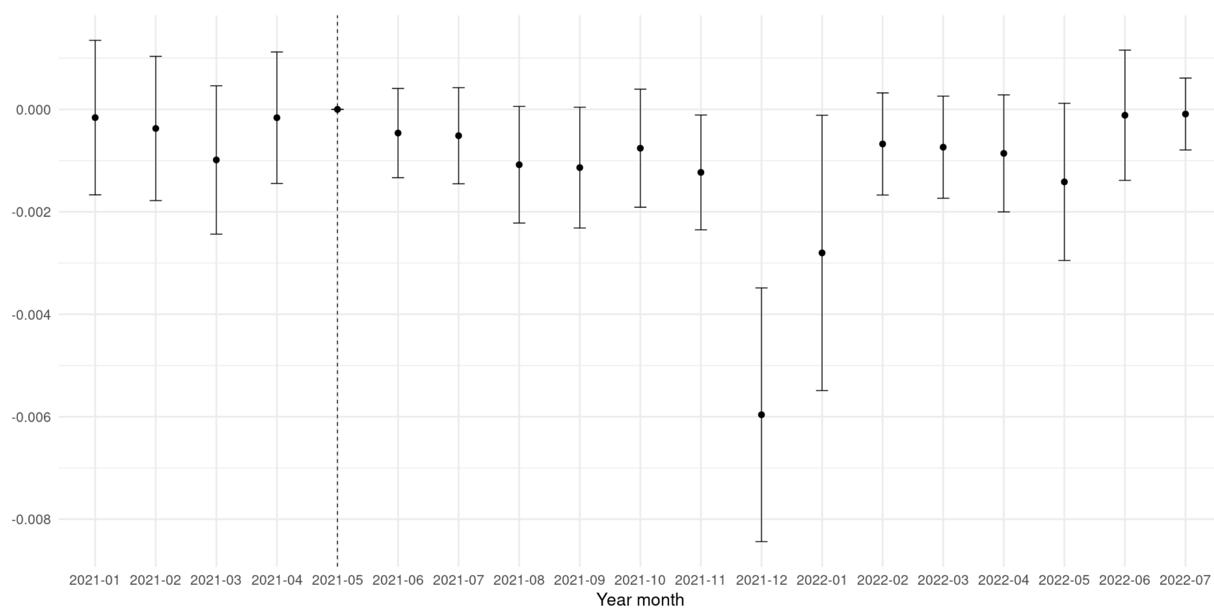


Figure 3.b : The Effects of Early Eligibility on Having Any COVID Infection Over Time

Note: The figures show the coefficients from the event study model (3). The outcomes denote the probability of having any outpatient visit (3.a) or a COVID infection (3.b). The black square indicates the relative difference in outcomes between the early and late eligibility group, accompanied by its 95% confidence interval. The vertical dotted line refers to the vaccine release date for the 12-15 age group.

Figure 4

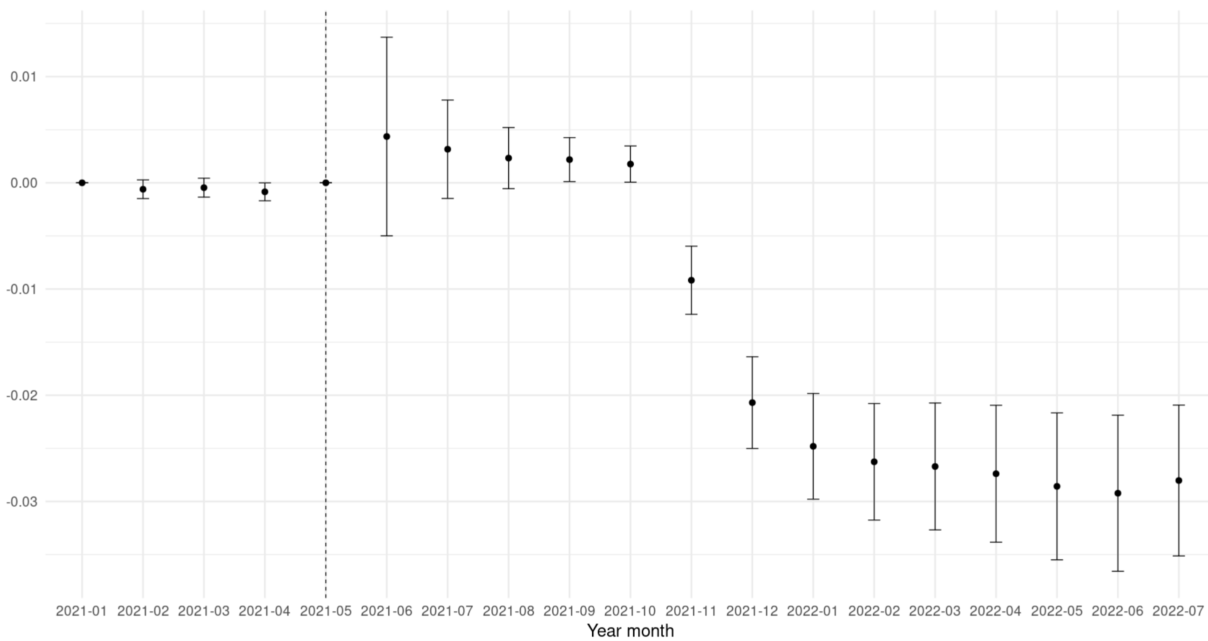


Figure 4.a : The LATE of vaccine uptake on having any outpatient visit over time

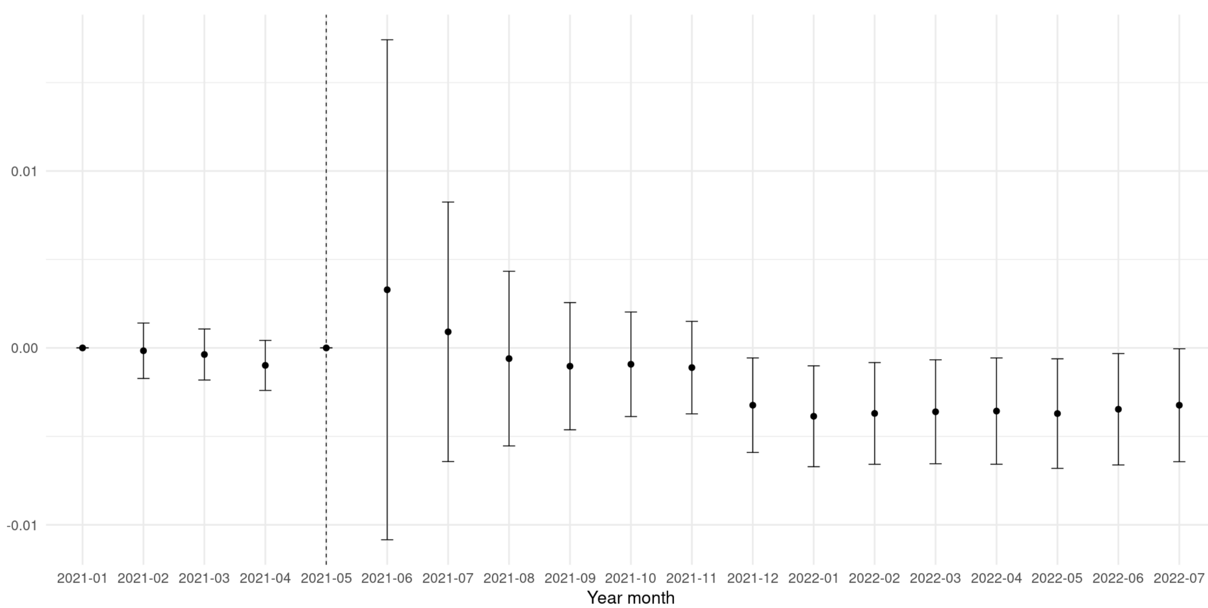


Figure 4.b : The LATE of vaccine uptake on having any COVID infection over time

Note: The figures show the coefficients from the DID model (5) when each additional month in post period is added into the model cumulatively. The outcomes denote the probability of having any outpatient visit (4.a) or a COVID infection (4.b). The black square indicates the local average treatment effects of vaccine uptake, accompanied by its 95% confidence interval. The vertical dotted line refers to the vaccine release date for the 12-15 age group.

Table 5

Table 5: Heterogeneous Effects of Early Eligibility and Vaccine Uptake

Panel A: Heterogeneous Effects by Student Race and Ethnicity

	All (1)	Asian (2)	Black (3)	Hispanic. (4)	White (5)	Other (6)
First stage effects	0.240***	0.327***	0.170***	0.260***	0.186***	0.247***
	(0.003)	(0.006)	(0.005)	(0.004)	(0.009)	(0.018)
Intention-to-Treat effects on having any outpatient visit:						
Early eligibility	−0.007***	−0.011***	−0.004***	−0.007***	−0.009***	0.003
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.005)
LATE on having any outpatient visit:						
Vaccine uptake	−0.028***	−0.033***	−0.024***	−0.027***	−0.047***	0.013
	(0.004)	(0.008)	(0.008)	(0.005)	(0.018)	(0.021)
Post-period mean	0.07	0.1	0.04	0.07	0.08	0.06
Percent decrease	40 %	33 %	60 %	38.6 %	58.8 %	21%
Observations	1,036,222	160,132	279,053	482,942	88,407	25,688

Panel B: Heterogeneous Effects by Borough of Residence

	All (1)	Bronx (2)	Brooklyn (3)	Manhattan (4)	Queens (5)	Staten Island (6)
First stage effects	0.240***	0.238***	0.228***	0.206***	0.272***	0.206***
	(0.003)	(0.005)	(0.006)	(0.009)	(0.006)	(0.011)
Intention-to-Treat effects on having outpatient visit:						
Early eligibility	−0.007***	−0.003*	−0.009***	−0.011***	−0.006***	−0.012***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
LATE on having any outpatient visit:						
Vaccine uptake	−0.028***	−0.011*	−0.039***	−0.056***	−0.021***	−0.058**
	(0.004)	(0.006)	(0.007)	(0.012)	(0.006)	(0.023)
Post-period mean	0.07	0.05	0.07	0.06	0.07	0.07
Percent decrease	40 %	22 %	55.7 %	93.3 %	30%	82.6%
Observations	1,036,222	278,882	316,027	98,629	287,204	55,480

Panel C: Heterogeneous Effects by Quartiles of Neighborhood COVID Infection Rate

	All (1)	First (2)	Second (3)	Third (4)	Fourth (5)
First stage effects	0.240***	0.239***	0.237***	0.248***	0.220***
	(0.003)	(0.006)	(0.006)	(0.005)	(0.009)
Intention-to-Treat effects on having outpatient visit:					
Early eligibility	−0.007***	−0.004***	−0.010***	−0.007***	−0.009***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
LATE on having any outpatient visit:					
Vaccine uptake	−0.028***	−0.016***	−0.041***	−0.028***	−0.041***
	(0.004)	(0.006)	(0.008)	(0.006)	(0.015)
Post-period mean	0.07	0.06	0.07	0.07	0.07
Percent decrease	40 %	26.7 %	58.6 %	40 %	58.6%
Observations	1,034,911	322,126	231,686	366,871	114,228

Note: The table presents the heterogeneous effects by race or ethnicity, borough of residence, and neighborhood COVID infection rate. Each column denotes stratified analysis by the respective category. Full vaccination status is the outcome for the first stage effects and having any outpatient is the outcome for ITT and LATE analysis. The model specification is the same as previous analyses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Appendix

1. Details of the key variables

Educational outcomes:

1. Absences:
   - Total tally of absences (over the entire school year)
   - Chronic absenteeism (missing more than 10% of all school days)
   - Number of medical visits on school days
   - Probability of any medical visits on school days
2. Test scores: Reading (English) and math in these forms:
   - Primary outcome: Test scores (standardized based on year and grade)
   - Whether a student is proficient in the subject (if test result is performance level 3 or 4)
   - Percent of ranking among all test takers in the same grade and year (based on scale scores)

Health outcomes: All health outcome variables are sourced from the NYS Medicaid (Salient) database.

1. Outpatient visits (the total number of visits and a binary version of if any use):
   - any outpatient office visits
   - COVID-related visits: outpatient visits with a COVID-related primary diagnosis (suggesting concurrent COVID infection or post-COVID conditions)
2. COVID infection:
   - the total number of infections
   - binary indicator of if infected
3. Emergency room visits (the total number of visits and a binary version of if any use):
   - any ED visits
   - COVID-related visits: ED visits with a COVID-related primary diagnosis (suggesting concurrent COVID infection or post-COVID conditions)
4. Hospitalizations (the total number of visits and a binary version of if any use):
5. COVID-related conditions: total number of diagnoses and having any diagnosis (vs having none)
   - Based on the following categories of diagnoses:
     - Circulatory system disorders

- Endocrine, nutritional, and metabolic disorders
- Digestive system disorders
- Musculoskeletal and connective tissue disorders
- Mental, behavioral, and neuro-developmental disorders
- Nervous system disorders
- Respiratory system disorders
- Genitourinary disorders
- Blood system disorders
- Long COVID

Early eligibility: students between the age of 12 and 12.5 as of the vaccine release date for age group 12-15 is the early eligibility compared to those between 11-11.5 who have to wait until November to become eligible. With their age being so close, I assume the early eligibility was randomly assigned between these two groups.

Vaccination status: vaccine records of students come from the City-wide Immunization Registry (CIR). I then create several variables measuring the COVID vaccine status as follows:

1. Ever fully vaccinated: if a student have completed two shots of either Pfizer or Moderna vaccines
2. Vaccinate before the 1st day of school: if a student has been fully vaccinated before the first day of school
3. Number of days a in a school year while fully vaccinated: a continuous variable measuring the number of days in a school year during which the student is fully vaccinated
4. Percent of days while fully vaccinated: a continuous variable measuring the percent of days in a school year during which the student is fully vaccinated
5. Vaccination status: binary variable created in the student-month panel data that indicates if a student is fully vaccinated in that month

Appendix table 1.1 ICD-10 diagnosis codes for variables created with Medicaid data

Variables	**ICD-10 Diganosis Codes**
Long COVID	X-B948, X-U099
Respiratory conditions	J45, J26, J15, J20.8, J40, J22, J98.9, J80
Blood system conditions	D47.3, D65, D68.3–D68.9, D69, D75.82, D75.83, M36.2
Circulatory system conditions	A36.81, B33.20, B33.22, B33.24, B58.81, I25.5, I40, I41, I42.0–I42.5, I42.8, I42.9, I43, I51.4, J10.82, J11.82, O90.3, G46, I67–I68 [except I67.0, I67.4, I82.40, I82.49, I82.4Y, I82.4Z, I82.62, I82.50, I82.59, I82.5Y, I82.5Z, and I82.72, I47,I48.0, I48.19, I48.21, I48.3–I48.9, and I49.1–I49.9]
Endocrine system conditions	E10, E11
Digestive system conditions	K20, K21, K22.0–K22.6, K22.89, K22.9, K23, K58, K59.0–K59.2, K59.89, K59.9, and K92.9
Muscuoskeletal system conditions	M60.0, M60.1, M60.8, M60.9, M61, M62, and M63
Mental health conditions	F06.4, F40.0, F40.1, F40.228, F40.230, F40.231, F40.232, F40.233, F40.240, F40.248, F40.8, F40.9, F41, F93.0, F06.30, F34.8, F34.9, F39
Nerves system conditions	F05, R40.0, R41, R44, A85, A86, G04, G05, R29, R26, R27, G26, and G50–G65
Genitourinary system conditions	N17, N19, N18, R88.0
COVID-related conditions	A22.1, A37.00, A37.01, A37.10, A37.11, A37.80, A37.81, A37.90, A37.91, A48.1, B25.0, B34.2, B44.0, B77.81, B97.29, J00, J01, J02, J03, J04, J05, J06, J09.X1, J09.X2, J09.X3, J09.X9, J10.00, J10.01, J10.08, J10.1, J10.82, J11.00, J11.08, and J11.82
COVID infection	A00, A02.0, A04.7, A04.8, A05.1, A06.6, A09, A37, A38, and A39

2. Descriptive statistics

Table A.2.1 Descriptive Statistics of Student Characteristics by Medicaid Enrollment Status

On Medicaid	No	Yes	Overall
Age as of release	11.75 *	11.76 *	11.76
	(0.52)	(0.52)	(0.52)
Male	0.51	0.51	0.51
	(0.50)	(0.50)	(0.50)
English learner	0.18 *	0.31 *	0.28
	(0.39)	(0.46)	(0.45)
Asian	0.15 *	0.15 *	0.15
	(0.35)	(0.36)	(0.36)
White	0.31 *	0.09 *	0.14
	(0.46)	(0.28)	(0.34)
Black	0.20 *	0.27 *	0.25
	(0.40)	(0.44)	(0.44)
Hispanic	0.29 *	0.47 *	0.43
	(0.45)	(0.50)	(0.49)
Other	0.05 *	0.02 *	0.03
	(0.22)	(0.16)	(0.17)
Bronx	0.13 *	0.27 *	0.24
	(0.34)	(0.44)	(0.43)
Brooklyn	0.28 *	0.30 *	0.30
	(0.45)	(0.46)	(0.46)
Manhattan	0.16 *	0.10 *	0.11
	(0.37)	(0.29)	(0.31)
Queens	0.33 *	0.28 *	0.29
	(0.47)	(0.45)	(0.45)
Staten Island	0.10 *	0.05 *	0.06
	(0.30)	(0.23)	(0.24)
Dist. to nearest vaccine site	443.71 *	389.15 *	401.69
	(357.08)	(278.05)	(298.95)
Ever fully vaccinated	0.64 *	0.56 *	0.58
	(0.48)	(0.50)	(0.49)
Vaccinate before 1st school month	0.27 *	0.24 *	0.25
	(0.45)	(0.43)	(0.43)
Ever boosted	0.20 *	0.10 *	0.12
	(0.40)	(0.30)	(0.33)
Tract-level characteristics			
Median.income	41179.83 *	27994.79 *	31024.34
	(21213.60)	(11702.15)	(15480.25)
Total population	5008.01 *	4957.78 *	4969.32
	(2862.54)	(2466.09)	(2562.68)
People with health insurance	4973.66 *	4925.66 *	4936.69
	(2825.38)	(2437.89)	(2532.24)
Total bedrooms	2145.74 *	1899.31 *	1955.93
	(1534.17)	(1066.22)	(1194.63)
N	16,249	54,469	70,718

Note: The table presents the student and their neighborhood level characteristics by Medicaid enrollment status as of . $*$ indicates the across group difference is significant based on a two sample T-test. Significance levels: $^{*}p<0.05$.

Table A.2.1 Descriptive Statistics of Health Outcomes by Early Vaccine Eligibility and Eventual Vaccination Status

	Eligibility on release date (Z_i)		Ever fully vaccinated (D_i)		Overall
	$Z_i = 0$	$Z_i = 1$	$D_i = 0$	$D_i = 1$	
Total num. COVID-related conditions	0.64 *	0.53 *	0.52 *	0.63 *	0.58
	(5.78)	(3.41)	(3.65)	(5.41)	(4.72)
If any COVID-related conditions	0.120 *	0.111 *	0.11 *	0.12 *	0.12
	(0.33)	(0.31)	(0.31)	(0.33)	(0.32)
Outpatient visits	1.36 *	1.21 *	1.08 *	1.44 *	1.28
	(2.31)	(2.25)	(2.04)	(2.44)	(2.28)
If any outpatient visits	0.47 *	0.43 *	0.41 *	0.48 *	0.45
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
COVID-related outpatient visits	0.12 *	0.10 *	0.09 *	0.12 *	0.11
	(0.48)	(0.43)	(0.42)	(0.48)	(0.45)
COVID infection	0.11 *	0.09 *	0.10	0.10	0.10
	(0.46)	(0.39)	(0.41)	(0.44)	(0.43)
Ever COVID infection	0.08 *	0.06 *	0.07	0.07	0.07
	(0.27)	(0.25)	(0.26)	(0.26)	(0.26)
COVID-related ED visits	0.02 *	0.01 *	0.02 *	0.01 *	0.02
	(0.15)	(0.13)	(0.15)	(0.13)	(0.14)
ED visits	0.13	0.13	0.14 *	0.12 *	0.13
	(0.52)	(0.56)	(0.58)	(0.51)	(0.54)
Ever ED visits	0.09	0.09	0.09 *	0.08 *	0.09
	(0.28)	(0.28)	(0.29)	(0.28)	(0.28)
Hospitalizations	0.04	0.03	0.05 *	0.03 *	0.04
	(1.41)	(0.36)	(1.49)	(0.34)	(1.02)
Ever hospitalized	0.01	0.01	0.01 *	0.01 *	0.01
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)
Num. of students	26,735	27,803	23,817	30,721	54,538

Note: The table presents the mean and standard deviations (in parenthesis) of the health outcomes by early eligibility and eventual vaccination (as of July, 2023) status. All health outcomes are derived from NYS Medicaid and aggregated through the 21-22 school year. $*$ indicates the across group difference is significant based on a two sample T-test. Significance levels: $^*p<0.05$.

Table A.2.2 Descriptive statistics of detailed health outcomes by early vaccine eligibility and eventual vaccination status

	Eligibility on release date		Ever fully vaccinated		Overall
	$Z_i = 0$	$Z_i = 1$	$D_i = 0$	$D_i = 1$	
COVID-related health conditions					
Total diagnoses	0.64 *	0.53 *	0.52 *	0.63 *	0.58
	(5.78)	(3.41)	(3.65)	(5.41)	(4.72)
If any	0.120 *	0.111 *	0.11 *	0.12 *	0.17
	(0.33)	(0.31)	(0.31)	(0.33)	(0.37)
COVID-related health conditions by categories or affected systems:					
Circulatory	0.01	0.00	0.01	0.01	0.01
	(0.83)	(0.13)	(0.31)	(0.73)	(0.59)
Musculoskeletal	0.02	0.01	0.02	0.01	0.02
	(0.69)	(0.69)	(0.86)	(0.52)	(0.69)
Respiratory	0.18 *	0.14 *	0.15	0.17	0.16
	(1.98)	(0.96)	(1.01)	(1.86)	(1.55)
Endocrine	0.06	0.03	0.03	0.05	0.04
	(3.47)	(1.11)	(1.16)	(3.24)	(2.55)
Digestive	0.05	0.03	0.02	0.05	0.04
	(2.14)	(0.26)	(0.30)	(2.00)	(1.51)
Mental health	0.29	0.26	0.24 *	0.30 *	0.28
	(3.24)	(2.60)	(2.81)	(3.02)	(2.93)
Nervous	0.04	0.04	0.04	0.04	0.04
	(0.66)	(1.05)	(0.99)	(0.79)	(0.88)
Genitourinary	0.00	0.00	0.00	0.00	0.00
	(0.09)	(0.06)	(0.09)	(0.06)	(0.07)
Blood	0.01	0.00	0.00	0.01	0.00
	(0.24)	(0.19)	(0.21)	(0.22)	(0.22)
N	26,735	27,803	23,817	30,721	54,538

Note: The table presents the mean and standard deviations (in parenthesis) of the more detailed health outcomes by categories or affected systems. All health outcomes are derived from NYS Medicaid and aggregated through the 21-22 school year. $*$ indicates the across group difference is significant based on a two sample T-test. Significance levels: $^{*}p<0.05$.

Table A.2.2 Descriptive statistics of student health outcomes by early eligibility status

	Pre-period			Post-period		
Variable	$Z_i = 1$	$Z_i = 0$	Overall	$Z_i = 1$	$Z_i = 0$	Overall
Num. of outpatient visits	0.002 *	0.002 *	0.002	0.081 *	0.091 *	0.086
	(0.049)	(0.056)	(0.053)	(0.357)	(0.375)	(0.366)
Had outpatient visit	0.001 *	0.002 *	0.002	0.062 *	0.070 *	0.066
	(0.035)	(0.042)	(0.039)	(0.242)	(0.254)	(0.248)
Num. of COVID infections	0.007	0.007	0.007	0.006 *	0.007 *	0.007
	(0.115)	(0.108)	(0.112)	(0.094)	(0.106)	(0.100)
Had COVID infection	0.006	0.006	0.006	0.005 *	0.006 *	0.005
	(0.074)	(0.077)	(0.076)	(0.070)	(0.077)	(0.074)
Num. of ED visits	0.005	0.006	0.006	0.009	0.009	0.009
	(0.083)	(0.083)	(0.083)	(0.106)	(0.106)	(0.106)
Had ED visit	0.005	0.005	0.005	0.008 *	0.008 *	0.008
	(0.070)	(0.073)	(0.071)	(0.089)	(0.091)	(0.090)
Num. of hospitalizations	0.002	0.002	0.002	0.003 *	0.003 *	0.003
	(0.070)	(0.117)	(0.096)	(0.075)	(0.128)	(0.104)
Had hospitalization	0.001	0.001	0.001	0.001	0.001	0.001
	(0.033)	(0.033)	(0.033)	(0.036)	(0.036)	(0.036)
COVID-related:						
Num. of outpatient visits	0.006	0.006	0.006	0.007 *	0.008 *	0.008
	(0.084)	(0.087)	(0.085)	(0.091)	(0.100)	(0.096)
Have outpatient visit	0.005	0.005	0.005	0.006 *	0.008 *	0.007
	(0.070)	(0.074)	(0.072)	(0.079)	(0.087)	(0.083)
Num. of ED visits	0.001	0.001	0.001	0.001 *	0.001 *	0.001
	(0.028)	(0.027)	(0.027)	(0.032)	(0.037)	(0.035)
Had ED visit	0.001	0.001	0.001	0.001 *	0.001 *	0.001
	(0.025)	(0.025)	(0.025)	(0.031)	(0.035)	(0.033)
COVID-related health conditions:						
Total number	0.051 *	0.059 *	0.055	0.044 *	0.054 *	0.049
	(0.456)	(0.552)	(0.505)	(0.397)	(0.543)	(0.474)
Probability of having any	0.023 *	0.026 *	0.024	0.023 *	0.026 *	0.024
	(0.150)	(0.158)	(0.154)	(0.150)	(0.158)	(0.154)
N	111,212	106,940	218,152	417,045	401,025	818,070

Note: The table presents the mean and standard deviations (in parenthesis) of the main health outcomes. All health outcomes are derived from NYS Medicaid and on the student-month level, with date of service covering between Jan. 2021 and July 2022. The pre-period refers to Jan. 2021 to May 2021 and the post-period refers to June 2021 to July 2022. $*$ indicates the across group difference is significant based on a two sample T-test. Significance levels: *p<0.05.

3. Indirect effects of vaccine uptake on health outcomes

Appendix table 3 the indirect effects of vaccines on student health outcomes

	Dependent variable:					
	End of school year outcomes		During school outcomes		During school before Nov.	
	COVID infection	Outpatient visits	COVID infection	Outpatient visits	COVID infection	Outpatient visits
	(1)	(2)	(3)	(4)	(5)	(6)
Indirect effects	−0.004	0.011	−0.00002	0.001	−0.0003	0.0002
	(0.005)	(0.052)	(0.0005)	(0.002)	(0.0003)	(0.001)
Observations	24,227	24,227	460,313	460,313	266,497	266,497
Note:						*p<0.1; **p<0.05; ***p<0.01

4. Class size as a potential moderator

Appendix table 4 the potentially moderating effects of class size on student health outcomes

	Dependent variable:					
	Num. of outpatient visits			Any COVID infection		
	(1)	(2)	(3)	(4)	(5)	(6)
Early Eligibility	−0.130***	−0.153***	−0.148***	−0.010***	−0.012***	−0.014***
	(0.030)	(0.023)	(0.020)	(0.003)	(0.002)	(0.002)
Above median class size	0.046	0.019		−0.002	−0.005*	
	(0.034)	(0.024)		(0.004)	(0.003)	
Early eligibility X Above median class size	−0.051			−0.006		
	(0.045)			(0.005)		
Observations	43,613	43,613	54,538	43,613	43,613	54,538
Note:						*p<0.1; **p<0.05; ***p<0.01

5. Results with other educational outcomes

5.1 Main model model with various educational outcomes

Appendix table 5.1 the effects of vaccines on other educational outcomes

	Dependent variable:					
	Reading			Math		
	If proficient	% ranking	Scale score	If proficient	% ranking	Scale score
	(1)	(2)	(3)	(4)	(5)	(6)
Intention-to-Treat:						
Early eligibility	0.063***	0.296	1.583***	0.027***	0.981***	2.125***
	(0.004)	(0.234)	(0.163)	(0.005)	(0.248)	(0.18)
LATE						
Vaccine uptake	0.021***	0.099	0.531***	0.009***	0.329***	0.712***
(per 10% days)	(0.001)	(0.079)	(0.055)	(0.002)	(0.082)	(0.060)
Observations	48,542	48,542	48,542	45,650	45,650	45,650
Note:						*p<0.1; **p<0.05; ***p<0.01

5.2 Heterogeneity in educational outcomes by race or ethnicity

Appendix table 5.2 the heterogeneous effects of vaccines on education outcomes by student race or ethnicity

	Analysis stratified by students' race or ethnicity:				
	Asian	Black	Hispanic	White	Other
First stage effects					
Early eligibility	0.327***	0.170***	0.260***	0.186***	0.247***
	(0.006)	(0.005)	(0.004)	(0.009)	(0.018)
Standardized math test score					
Group mean	0.680	−0.317	−0.254	0.246	−0.036
Early eligibility	0.048**	0.002	0.037***	0.107***	0.131**
	(0.021)	(0.016)	(0.012)	(0.030)	(0.058)
Percentile ranking in math scores					
Group mean	68.685	39.498	41.133	56.347	47.778
Early eligibility	1.237**	0.046	0.924***	3.230***	3.994**
	(0.578)	(0.482)	(0.353)	(0.878)	(1.719)
Observations	7,555	12,085	21,380	3,651	979
Standardized reading test score					
Group mean	0.470	−0.231	−0.244	0.163	0.015
Early eligibility	0.016	0.011	0.007	0.070**	0.077
	(0.021)	(0.016)	(0.012)	(0.030)	(0.054)
Percentile ranking in reading scores					
Group mean	62.25	41.16	40.88	52.989	48.61
Early eligibility	0.472	0.171	−0.024	2.012**	2.104
	(0.601)	(0.446)	(0.342)	(0.874)	(1.573)
Observations	8,017	12,917	22,642	3,911	1,055

Note: *p<0.1; **p<0.05; ***p<0.01

6. Results with other health outcomes

Appendix table 6.1: The Effects of Early Eligibility and Vaccine Uptake on Aggregrated Health Outcomes Over the 2122 School Year

	Early eligibility	Vaccine uptake	
Dependent variables (rows):	Intention-to-treat	LATE (per 10% days)	Overall mean
Total num. diagnoses	-0.112^{***}	-0.038^{***}	0.58
	(0.040)	(0.014)	
If any diagnosis	-0.009^{***}	-0.003^{***}	0.17
	(0.003)	(0.001)	
Digestive system	-0.021	-0.007	0.05
	(0.013)	(0.005)	
Mental health	-0.024	-0.008	0.29
	(0.025)	(0.009)	
Respiratory system	-0.035^{***}	-0.012^{***}	0.18
	(0.013)	(0.005)	
Endocrine system	-0.025	-0.009	0.06
	(0.022)	(0.008)	
Genitourinary system	-0.001	-0.0003	0.00
	(0.001)	(0.0002)	
Musculoskeletal	-0.003	-0.001	0.02
	(0.006)	(0.002)	
Nervous system	0.007	0.002	0.04
	(0.008)	(0.003)	
Circulatory system	-0.006	-0.002	0.01
	(0.005)	(0.002)	
Blood system	-0.003	-0.001	0.01
	(0.002)	(0.001)	
Observations	54,538	54,538	

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix table 6.2: The Effects of Early Eligibility on Health Outcomes with Student-month Observations

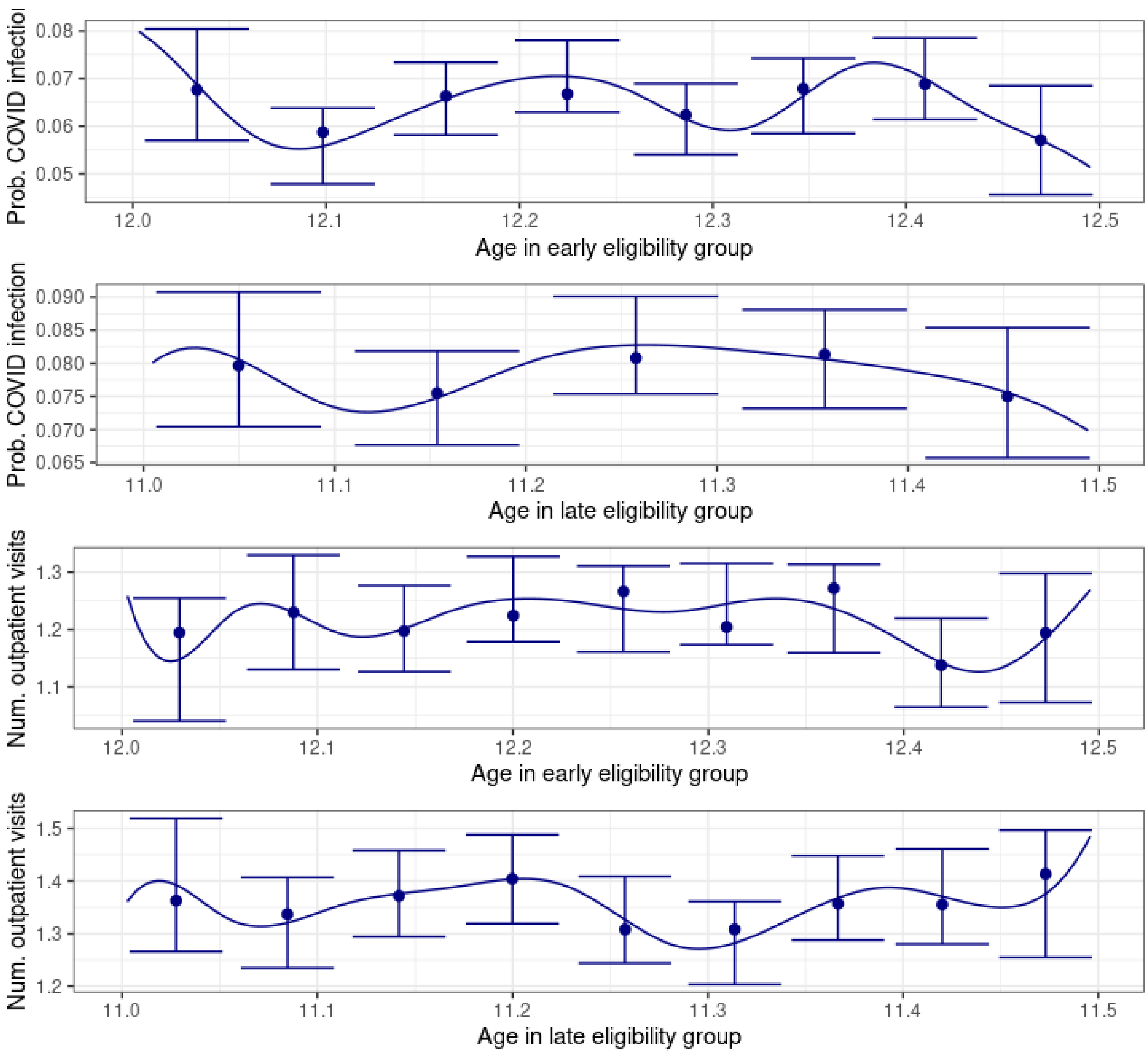
	Independent variable: Early Eligibility
Total num. health conditions	−0.001
	(0.003)
Conditions by each category:	
Blood system	0.0004*
	(0.0002)
Circulatory system	0.0003
	(0.0003)
Digestive system	0.0003
	(0.0003)
Endocrine system	−0.001
	(0.001)
Genitourinary system	0.00000
	(0.0001)
Mental health	0.002
	(0.002)
Musculoskeletal system	0.00003
	(0.0005)
Nervous system	0.0002
	(0.001)
Respiratory system	−0.002
	(0.001)
Observations	1,036,222
Note:	*p<0.1; **p<0.05; ***p<0.01

7. Placebo and Robustness Checks

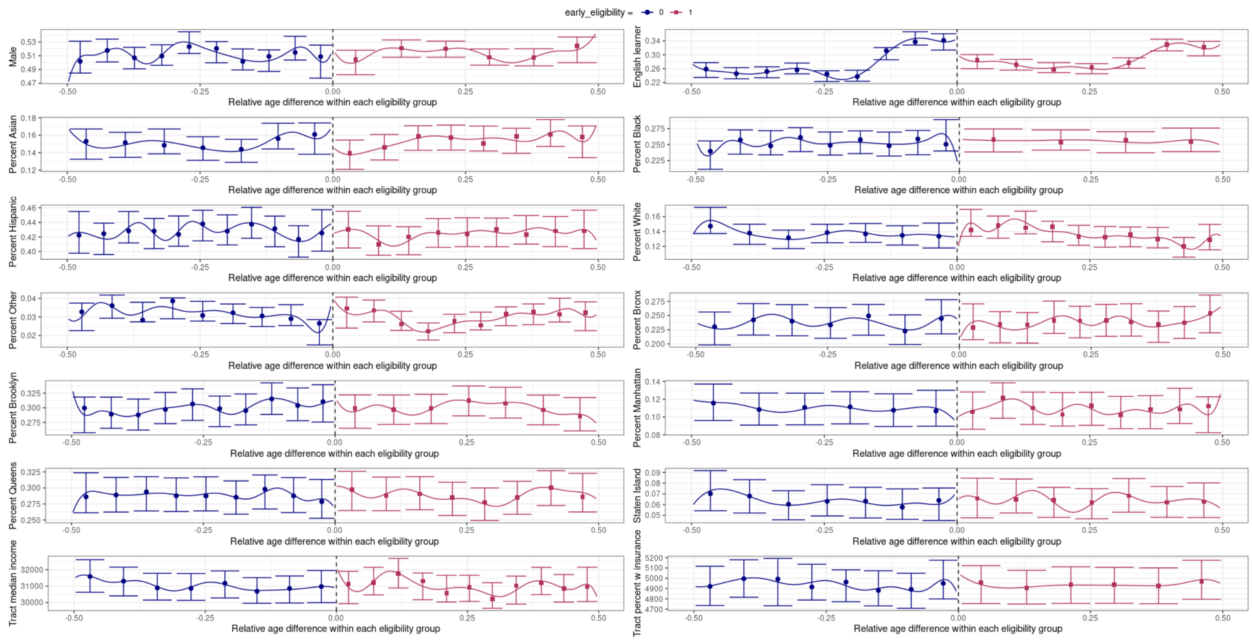
7.1 Balance of Student Characteristics and Historical Outcomes by Early Eligibility Status

Appendix table 7.1.1 : Balance of student characteristics by early eligibility status

	Early eligibility			Alternative definition		
Variable	$Z = 1$	$Z = 0$	Overall	$D = 1$	$D = 0$	Overall
Age as of vaccine release	12.252 *	11.253 *	11.762	12.506 *	11.506 *	12.016
	(0.144)	(0.145)	(0.520)	(0.287)	(0.286)	(0.576)
Male	0.515	0.514	0.514	0.514	0.515	0.515
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
English learner	0.316 *	0.306 *	0.311	0.321 *	0.329 *	0.325
	(0.465)	(0.461)	(0.463)	(0.467)	(0.470)	(0.468)
Student grade						
Grade 6	0.09 *	0.78 *	0.43	0.37 *	0.50 *	0.43
	(0.28)	(0.41)	(0.49)	(0.48)	(0.50)	(0.49)
Grade 7	0.70 *	0.22 *	0.47	0.51 *	0.41 *	0.47
	(0.46)	(0.41)	(0.50)	(0.50)	(0.49)	(0.50)
Grade 8	0.21 *	0.00 *	0.11	0.12 *	0.09 *	0.11
	(0.41)	(0.02)	(0.31)	(0.33)	(0.28)	(0.31)
School type						
Junior or high school	0.74 *	0.67 *	0.70	0.73 *	0.67 *	0.70
	(0.44)	(0.47)	(0.46)	(0.44)	(0.47)	(0.46)
K-8 or K-12 school	0.26 *	0.33 *	0.30	0.27 *	0.33 *	0.30
	(0.44)	(0.47)	(0.46)	(0.44)	(0.47)	(0.46)
Student Race or Ethnicity						
Asian	0.155	0.154	0.155	0.160 *	0.156 *	0.158
	(0.362)	(0.361)	(0.362)	(0.367)	(0.363)	(0.365)
Black	0.270	0.269	0.269	0.266	0.266	0.266
	(0.444)	(0.444)	(0.444)	(0.442)	(0.442)	(0.442)
Hispanic	0.466	0.466	0.466	0.461	0.466	0.463
	(0.499)	(0.499)	(0.499)	(0.498)	(0.499)	(0.499)
White	0.085	0.085	0.085	0.089	0.088	0.088
	(0.280)	(0.279)	(0.279)	(0.285)	(0.283)	(0.284)
Other	0.024	0.026	0.025	0.024	0.025	0.025
	(0.153)	(0.158)	(0.155)	(0.153)	(0.157)	(0.155)
Borough of residence						
Bronx	0.270	0.269	0.269	0.265	0.270	0.268
	(0.444)	(0.444)	(0.444)	(0.442)	(0.444)	(0.443)
Brooklyn	0.303	0.306	0.304	0.305	0.305	0.305
	(0.459)	(0.461)	(0.460)	(0.460)	(0.460)	(0.460)
Manhattan	0.096	0.095	0.095	0.096	0.096	0.096
	(0.295)	(0.293)	(0.294)	(0.294)	(0.294)	(0.294)
Queens	0.278	0.277	0.278	0.279	0.276	0.277
	(0.448)	(0.448)	(0.448)	(0.448)	(0.447)	(0.448)
Staten Island	0.054	0.053	0.054	0.056	0.054	0.055
	(0.226)	(0.225)	(0.225)	(0.229)	(0.225)	(0.227)
Dist. to nearest vaccine site	389.341	388.959	389.154	388.757	388.022	388.396
	(276.889)	(279.259)	(278.051)	(276.720)	(278.857)	(277.768)
Tract-level characteristics						
Median income	28069.311	27917.276	27994.785	28114.728 *	27949.461 *	28033.727
	(11637.567)	(11768.663)	(11702.151)	(11694.178)	(11746.671)	(11720.174)
Total population	4966.394	4948.827	4957.783	4972.498	4957.257	4965.028
	(2486.437)	(2444.757)	(2466.087)	(2492.510)	(2473.293)	(2483.110)
People with health insurance	4933.773	4917.228	4925.663	4939.960	4925.623	4932.933
	(2457.077)	(2417.800)	(2437.894)	(2461.963)	(2445.275)	(2453.798)
Total bedrooms	1904.808	1893.594	1899.311	1907.051	1897.924	1902.578
	(1076.624)	(1055.274)	(1066.217)	(1082.728)	(1073.099)	(1078.024)
Total positive cases	26682.515	26681.356	26681.947	26711.935	26686.033	26699.240
	(2972.023)	(2977.629)	(2974.745)	(3009.316)	(2978.763)	(2994.395)
N	27,769	26,700	54,469	56,870	54,667	111,537



Appendix figure 7.1.2 The non-parametric distribution of student health outcomes by age in each eligibility group



Appendix figure 7.1.3 The non-parametric distribution of student characteristics by age in each eligibility group

7.2 Testing pretrends and pre-COVID test scores

Appendix table 7.2.1 Extended pre-period event study coefficients

	Dependent variable:
	COVID infections
Interaction term by each month	
Sep 2020	−0.00005
	(0.001)
Oct 2020	−0.0002
	(0.001)
Nov 2020	−0.001
	(0.001)
Dec 2020	−0.0005
	(0.001)
Jan 2021	−0.0001
	(0.001)
Feb 2021	0.00000
	(0.001)
Mar 2021	−0.002
	(0.001)
Apr 2021	−0.0002
	(0.001)
Observations	492,651
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix table 7.2.2 the correlation between early eligibility and pre-COVID test scores

	Dependent variable:					
	Standardized test scores		Percentile ranking		If proficient in	
	reading	math	reading	math	reading	math
Early eligibility	−0.001	−0.009	0.010***	−0.002	−0.054***	−0.046***
	(0.009)	(0.009)	(0.003)	(0.003)	(0.005)	(0.005)
Observations	42,558	40,359	42,558	40,359	42,558	40,359
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix table 7.2.3 Selection into testing for the 21-22 school year

	Dependent variable:	
	Math testing	Tested reading
	(1)	(2)
Early eligibility	0.075***	−0.001
	(0.003)	(0.003)
Male	0.004	0.022***
	(0.003)	(0.003)
English learner	−0.044***	−0.019***
	(0.004)	(0.003)
Student race or ethnicity		
Reference group: Hispanic		
Asian	−0.052***	−0.055***
	(0.005)	(0.004)
Black	0.0003	0.001
	(0.005)	(0.004)
Other	0.102***	0.106***
	(0.013)	(0.012)
White	0.041***	0.042***
	(0.007)	(0.006)
Borough of residence		
Brooklyn	0.024***	0.015***
	(0.006)	(0.005)
Manhattan	0.039***	0.023**
	(0.011)	(0.009)
Queens	0.013**	−0.011**
	(0.006)	(0.005)
Staten Island	0.034***	0.021**
	(0.009)	(0.009)
Constant	0.092***	0.089***
	(0.009)	(0.009)
Observations	54,538	54,538
Note:		*p<0.1; **p<0.05; ***p<0.01

7.3 Various alternative model specifications

End-of-school-year results

Appendix table 7.3.1 Various specification of 1st stage

	Dependent variable:				
	Percentage days fully vaccinated				
	(1)	(2)	(3)	(4)	(5)
Early eligibility	2.920***	2.916***	2.915***	2.883***	2.915***
	(0.038)	(0.036)	(0.036)	(0.037)	(0.037)
Student control		X	X	X	X
Neighborhood control			X	X	X
School fixed effects				X	
Tract fixed effects					X
Observations	54,739	54,546	54,538	54,538	54,538
Adjusted R^2	0.124	0.204	0.206	0.227	0.224
Note:			*p<0.1; **p<0.05; ***p<0.01		

Appendix table 7.3.2 Various specification of ITT on health outcome

	Dependent variable:				
	Any COVID infection				
	(1)	(2)	(3)	(4)	(5)
Early eligibility	−0.014***	−0.014***	−0.014***	−0.014***	−0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Student control		X	X	X	X
Neighborhood control			X	X	X
School fixed effects				X	
Tract fixed effects					X
Observations	54,739	54,546	54,538	54,538	54,538
Adjusted R^2	0.001	0.003	0.004	0.013	0.009
Note:			*p<0.1; **p<0.05; ***p<0.01		

Appendix table 7.2.3 Various specification of ITT on educational outcome

	Dependent variable:				
	Math test score				
	(1)	(2)	(3)	(4)	(5)
Early Eligibility	0.033***	0.037***	0.037***	0.035***	0.035***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
Student control		X	X	X	X
Neighborhood control			X	X	X
School fixed effects				X	
Tract fixed effects					X
Observations	45,785	45,657	45,650	45,650	45,650
Adjusted R^2	0.0003	0.157	0.161	0.297	0.185
Note:			*p<0.1; **p<0.05; ***p<0.01		

During-of-school-year results

Appendix table 7.3.4 Various specification of 1st stage

	Dependent variable:				
	Fully vaccinated				
	(1)	(2)	(3)	(4)	(5)
Early Eligibility	0.240***	0.240***	0.240***	0.240***	0.240***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Student control		X	X	X	X
Neighborhood control			X	X	X
School fixed effects				X	
Tract fixed effects					X
Observations	1,040,041	1,036,374	1,036,222	1,036,222	1,036,222
Adjusted R^2	0.155	0.187	0.188	0.201	0.204
Note:			*p<0.1; **p<0.05; ***p<0.01		

Appendix table 7.3.5 Various specification of ITT on health outcome

	Dependent variable:				
	Any COVID infection				
	(1)	(2)	(3)	(4)	(5)
Early Eligibility	-0.001^{*}	-0.001^{**}	-0.001^{**}	-0.001^{**}	-0.001^{**}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Student control		X	X	X	X
Neighborhood control			X	X	X
School fixed effects				X	
Tract fixed effects					X
Observations	1,040,041	1,036,374	1,036,222	1,036,222	1,036,222
Adjusted R^2	0.00004	0.0002	0.0002	0.003	0.001
Note:					*p<0.1; **p<0.05; ***p<0.01

7.4 Main Results using Alternative Definitions of Early Eligibility

Appendix table 7.4.1 Main Results on Educational Outcomes Using Alternative Definition of Early Eligibility

			Absence-related outcomes:	
Intention-to-Treat	Absences	Chronic absenteeism	Medical visits on school days	Had medical visits on school days
Early eligibility	0.337^{***}	0.007^{***}	-0.099^{***}	-0.028^{***}
	(0.080)	(0.002)	(0.016)	(0.003)
Local Average Treatment Effects:				
Per 10 % of days vaccinated	0.173^{***}	0.004^{***}	-0.051^{***}	-0.014^{***}
	(0.042)	(0.001)	(0.008)	(0.002)
N (Students)	108,902	108,902	111,695	111,695
			Test scores:	
Intention-to-Treat	% ranking math	% ranking reading	Standardized math	Standardized reading
Early eligibility	1.588^{***}	0.375^{**}	0.056^{***}	0.016^{***}
	(0.188)	(0.164)	(0.006)	(0.006)
Local Average Treatment Effects:				
Per 10 % of days vaccinated	0.828^{***}	0.190^{**}	0.029^{***}	0.008^{***}
	(0.097)	(0.083)	(0.003)	(0.003)
N (Students)	87,210	98,902	87,210	98,902

*Note:*Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Appendix table 7.4.2 Effects of early eligibility and vaccine uptake on health outcomes

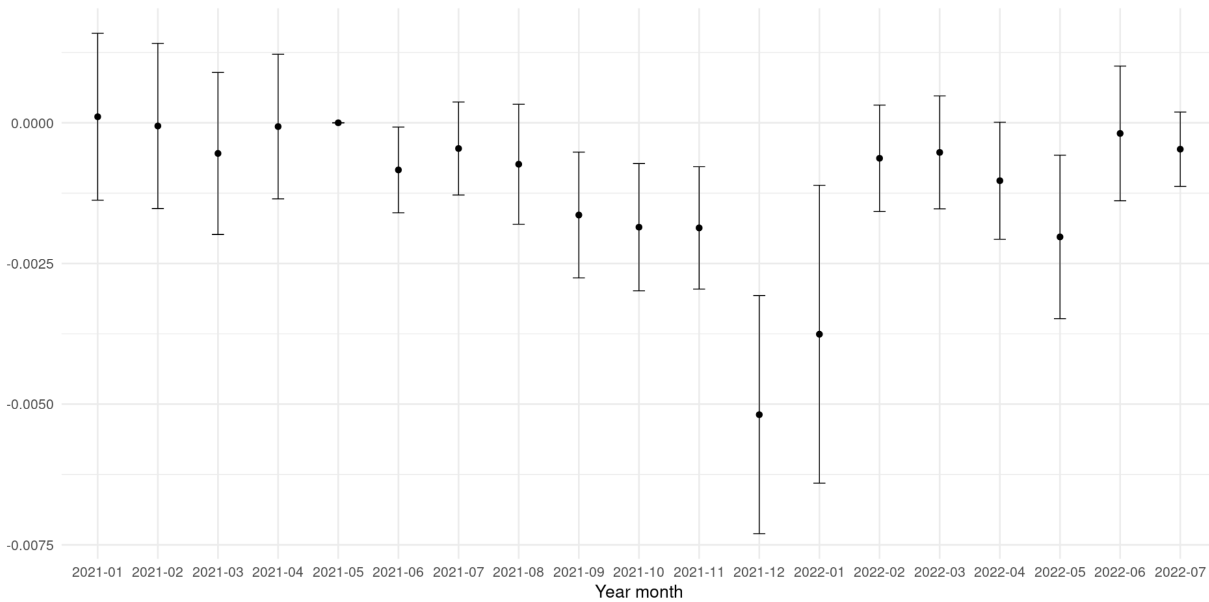
	Early eligibility	Vaccine uptake	Overall mean
Dependent variables:	Intention-to-treat	Intention-to-treat	
Outpatient visits	-0.102^{***}	-0.053^{***}	1.25
	(0.013)	(0.007)	
COVID-related outpatient visits	-0.013^{***}	-0.007^{***}	0.11
	(0.003)	(0.001)	
Ever COVID infection	-0.009^{***}	-0.005^{***}	0.07
	(0.001)	(0.001)	
ED visits	-0.004	-0.002	0.13
	(0.003)	(0.002)	
COVID-related ED visits	-0.003^{***}	-0.001^{***}	0.02
	(0.001)	(0.0004)	
Hospitalizations	-0.003	-0.001	0.04
	(0.005)	(0.003)	
Had COVID-related health condition	-0.007^{***}	-0.004^{***}	0.11
	(0.002)	(0.001)	
N (Students)	111,695	111,695	111,695

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01.

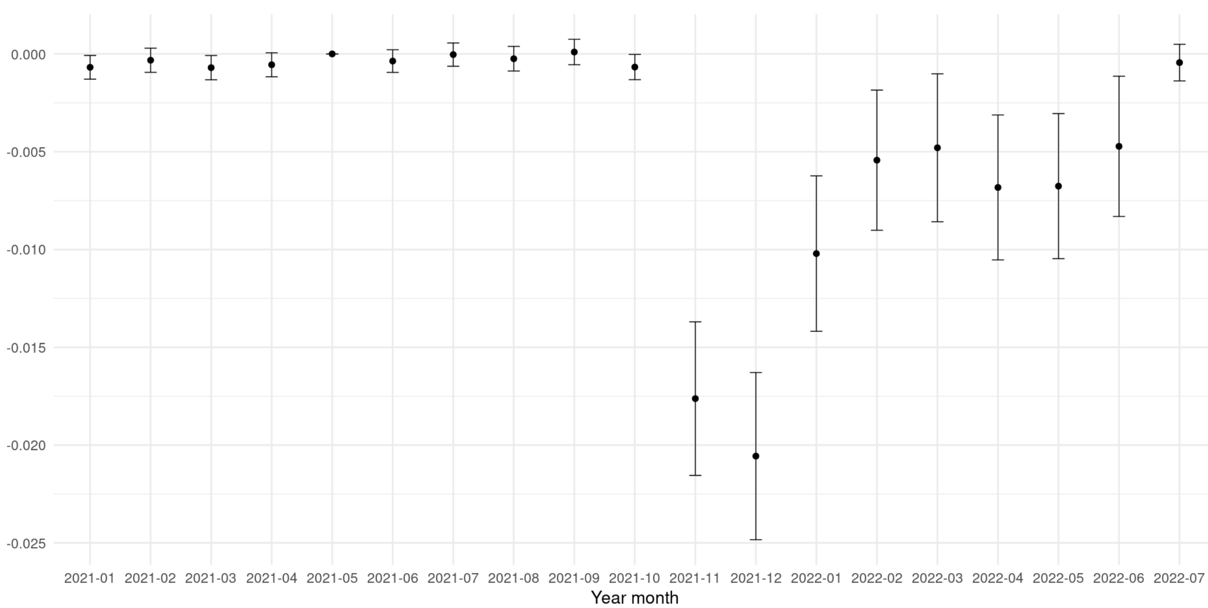
Appendix table 7.4.3 The effects of early eligibility and vaccine uptake on various health outcomes

	Indicators of health outcomes:						
	Outpatient visit	COVID infection	COVID-related outpatient visit	ED visit	COVID-related ED visit	Hospitalized	COVID-related health conditions
Post-period mean	0.04	0.005	0.007	0.009	0.001	0.001	0.024
Difference-in-differences model							
Intention-to-Treat	−0.005***	−0.001**	−0.0004	0.0001	−0.0002**	−0.0001	−0.001
	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.001)
LATE of vaccine uptake	−0.028***	−0.004**	−0.002	0.0004	−0.001**	−0.0004	−0.003
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Post-period event study coefficients							
Jun 2021	−0.0004	−0.001**	−0.00003	−0.001*	0.001	0.0002	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.001)	(0.0003)	(0.001)
July 2021	−0.00003	−0.0003	−0.0003	−0.001*	0.001	−0.0001	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
Aug. 2021	−0.0002	−0.001*	−0.00002	−0.0002	0.001	−0.0003	−0.0002
	(0.0003)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
Sep. 2021	0.0001	−0.001***	−0.0001	−0.002***	0.0005	0.0001	−0.002**
	(0.0003)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
Oct. 2021	−0.001**	−0.001**	0.0001	−0.002***	0.0004	−0.0002	−0.001
	(0.0003)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
Nov. 2021	−0.018***	−0.001***	−0.0002	−0.002***	0.0001	−0.0001	−0.001
	(0.002)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
Dec. 2021	−0.021***	−0.004***	−0.0004	−0.003***	−0.001	−0.0003	−0.005***
	(0.002)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.0003)	(0.001)
Jan. 2022	−0.010***	−0.003***	−0.001**	−0.001	−0.0004	−0.0003	−0.002*
	(0.002)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.001)
Feb. 2022	−0.005***	−0.001	−0.0002	−0.0004	0.001	−0.0003	−0.001
	(0.002)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
March 2022	−0.005**	−0.0005	−0.0002	−0.001	0.0001	0.0002	−0.0002
	(0.002)	(0.0003)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
Apr 2022	−0.007***	−0.001*	−0.0003	−0.002***	0.0003	−0.00001	−0.002
	(0.002)	(0.0004)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
May 2022	−0.007***	−0.001**	−0.0003	−0.0005	0.0003	0.0002	−0.002
	(0.002)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.001)
June 2022	−0.005**	−0.0003	−0.0003	−0.001	0.0003	−0.0002	−0.0003
	(0.002)	(0.0005)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)
July 2022	−0.0004	−0.0003	−0.00001	−0.0003	0.001	−0.0001	0.001
	(0.0005)	(0.0002)	(0.0002)	(0.0004)	(0.001)	(0.0002)	(0.001)
N (Students X months)	2,122,205	2,122,205	2,122,205	2,122,205	2,122,205	2,122,205	2,122,205
N (Students)	111,695	111,695	111,695	111,695	111,695	111,695	111,695

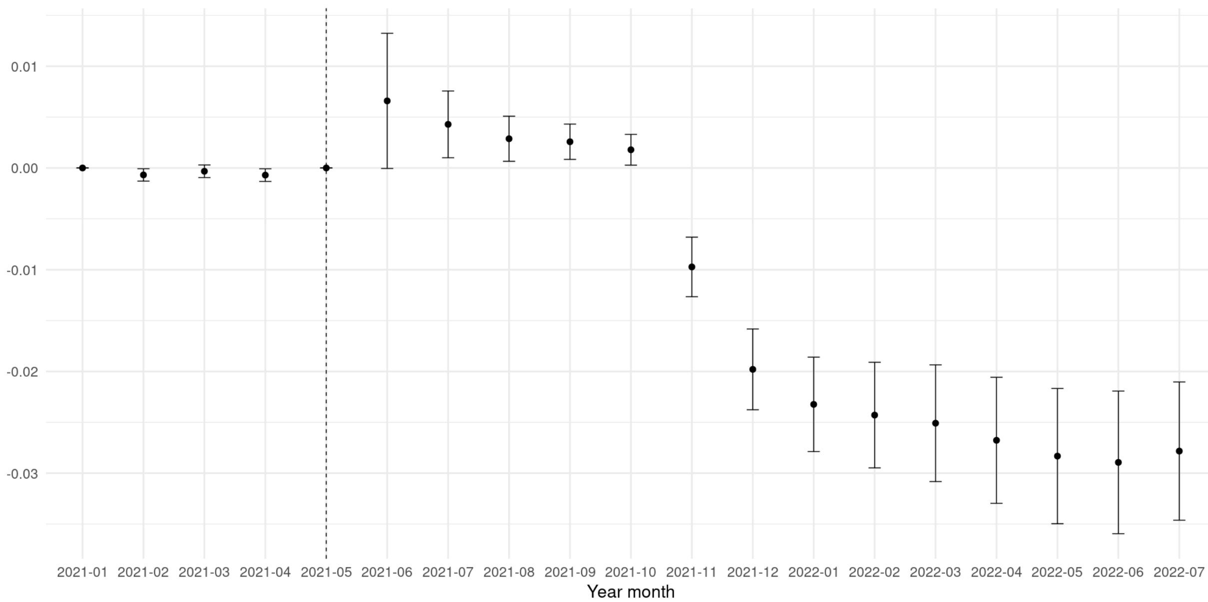
Note: The table presents both the coefficients of Intention-to-Treat (ITT) of early eligibility and Local Average Treatment Effect (LATE) of vaccine uptake on various health outcomes for the study duration (January 2021 to July 2022). Following these are the monthly coefficients from event studies for the post-period (June 2021 to July 2022), using May 2021 as the reference. Standard errors are robust and clustered by census tract. The analysis was conducted on the student-month level following equation (3), (4), and (5), with the student sample consistent with prior analyses. The outcome variables, derived from NYS Medicaid, indicate whether a specific health event or diagnosis occurred in that given month. Detailed definitions and relevant diagnosis codes provided in the appendix. Significance levels: *p<0.1; **p<0.05; ***p<0.01.



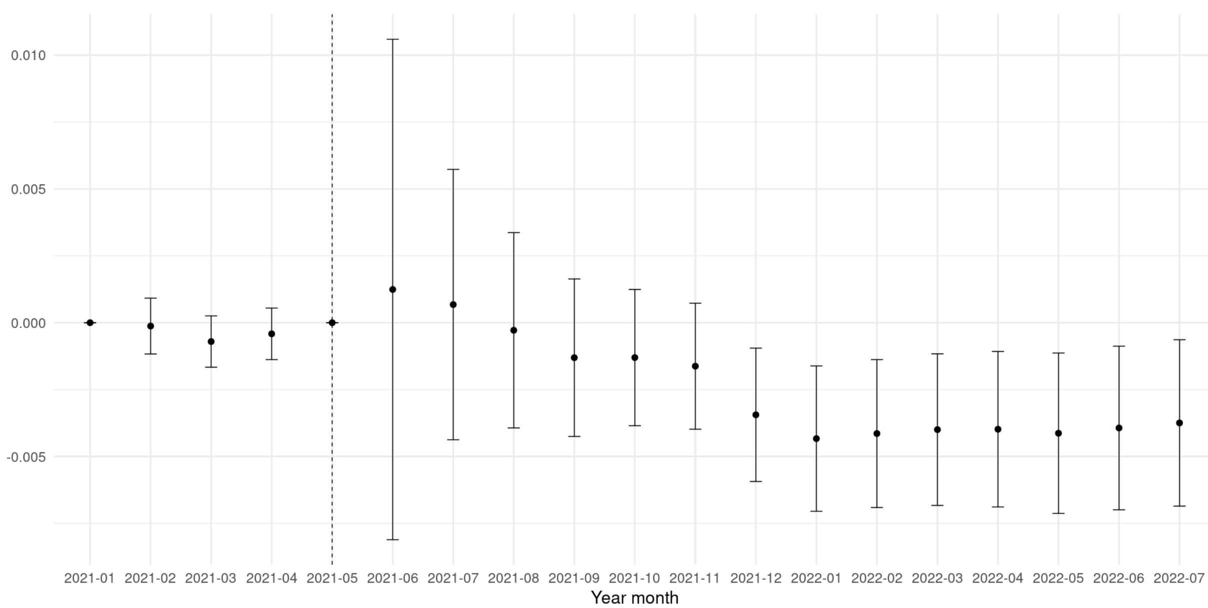
Appendix figure 7.4.1 The LATE of vaccine uptake on having any COVID infection over time



Appendix figure 7.4.2 The LATE of vaccine uptake on having any COVID infection over time



Appendix figure 7.3.3 The LATE of vaccine uptake on having any COVID infection over time



Appendix figure 7.4.4 The LATE of vaccine uptake on having any COVID infection over time

7.5 Educational results using non-Medicaid students

Appendix table 7.5.1

	Dependent variable:			
Non-Medicaid students:				
	Total count of absences	If chronically absent	Standardized test scores math	Standardized test scores reading
Early eligibility	0.097	0.005	-0.018	-0.037^{**}
	(0.155)	(0.004)	(0.015)	(0.015)
Overall mean	9.13	0.067	0.33	0.38
Observations	14,758	14,758	13,411	13,708
	If proficient in math	If proficient in reading	Percentile rank in math	Percentile rank in reading
Early eligibility	0.006	0.016^{***}	-0.292	-0.641
	(0.007)	(0.005)	(0.460)	(0.436)
Overall mean	0.73	0.089	59.7	58.72
Observations	13,411	13,708	13,411	13,708
All students:				
	Total count of absences	If chronically absent	Standardized test scores math	Standardized test scores reading
Early eligibility	0.030	0.003	0.021^{***}	0.001
	(0.097)	(0.003)	(0.008)	(0.007)
Observations	67,908	67,908	59,061	62,250
	If proficient in math	If proficient in reading	Percentile rank in math	Percentile rank in reading
Early eligibility	0.021^{***}	0.052^{***}	0.583^{**}	0.024
	(0.004)	(0.003)	(0.280)	(0.250)
Observations	59,061	62,250	59,061	62,250

Note: The table presents the results using equation (1) with the samples, including non-Medicaid students only and all students. Observations vary across models due to local missingness in the outcome variables. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

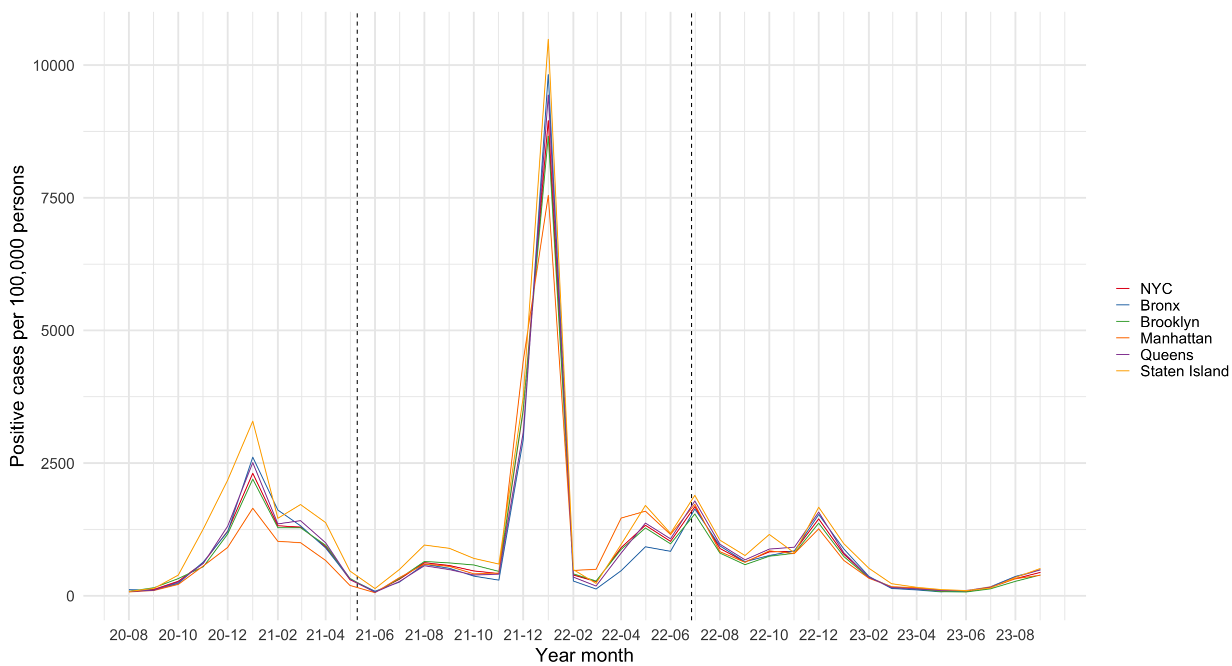
7.6 Randomly assigning post month

Appendix table 7.6.1 Using three random months draw as the vaccine release month

	Dependent variable:		
	Any COVID infection		
	Feb 2021	April 2022	May 2022
ITT	−0.001	0.001*	0.001
Observations	1,036,222	1,036,222	1,036,222
Note:	*p<0.1; **p<0.05; ***p<0.01		

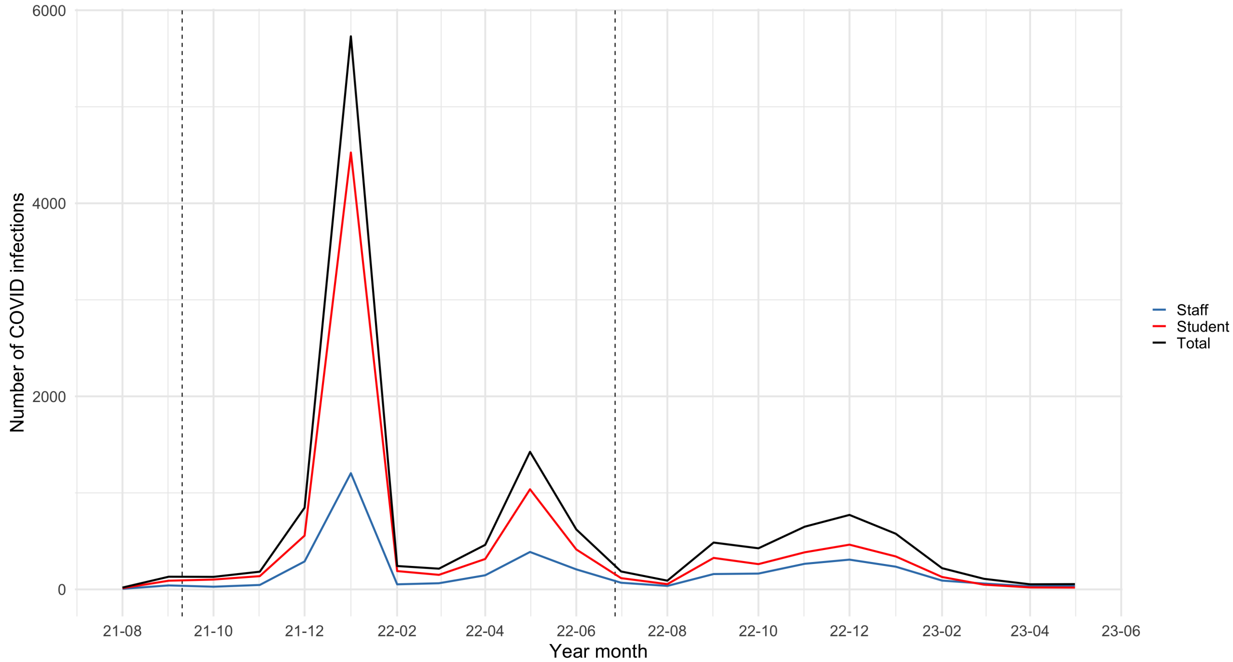
8. Cumulative COVID infection rate

8.1 City and borough level infection rate



Note: The figure shows the historical trends of COVID infection rate per 100,000 person of NYC and by all five boroughs. The data counts lab-confirmed COVID infection via PCR or Antibody tests, is published by the Department of Health. The vertical dashed lines indicate the time period under study in the during-school-year analysis, i.e., from vaccine release to the end of 21-22 school year.

8.2 School level infection rate



Note: The figure shows the historical trends of COVID infection rate in NYC public schools. The data counts lab-confirmed COVID infection via PCR or Antibody tests, is published by the Department of Health and Department of Education. The vertical dashed lines indicate the beginning and end of 21-22 school year.

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