Vaccines, Peers, and School Attendance:

Evidence from COVID

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Abstract

As vaccine coverage increasingly depends upon voluntary take-up, understanding how school peer vaccination affects own take-up is important for public health and schooling. Using linked administrative data from New York City Department of Education (NYCDOE) and vaccine records from the Department of Health and Mental Hygiene (DOHMH), this paper estimates the causal effect of peer vaccination on individual vaccine take-up and school attendance. The empirical strategy leverages the age-based rollout of COVID vaccine eligibility, using grademate eligibility rates at school start as an instrument for grademate vaccination rates. We find that a 10-percentage-point increase in grademate vaccination increases own vaccine take-up by 1.7 percentage points, raises attendance by 0.7 percentage points, and reduces chronic absenteeism by 2.9 percentage points. Effects differ by race and ethnicity, with larger attendance improvements for Black and Hispanic students, but there is little evidence of meaningful gender differences. Estimates are smaller when peers are defined more broadly as schoolmates, suggesting that peer effects operate most strongly through proximate school environments. The findings show that voluntary vaccination behavior generates spillovers not only in health decisions, but also in educational outcomes.

Keywords: vaccination; absenteeism; school health; COVID

1. Introduction

Rising vaccine skepticism and a shift towards optional vaccination policies pose significant public-health risks. Take-up of routine, and even mandatory, childhood vaccines has declined in recent years, leaving children more vulnerable to diseases once considered rare (Seither et al., 2024). Measles, once eliminated in the United States, reached a 34-year high in 2025 (Mathis et al., 2025). As vaccine coverage increasingly depends on voluntary participation, understanding how peer vaccination behavior shapes individual vaccination decisions is essential for effective policymaking.

Many factors shape whether families vaccinate their children. The benefits of vaccination depend on the risk of getting COVID and the expected consequences of infection, both with and without vaccination. Costs associated with vaccination include not only vaccine prices but also side effects and institutional barriers to access, such as eligibility rules. Families also weigh school-related consequences, including the costs of illness-related absences. Institutional trust, cultural beliefs, and information shape these costs and benefits, and peers can influence all three.

Peer vaccination influences vaccination decisions through several channels. First, peer vaccination shapes the risk of getting COVID: higher peer vaccination rates reduce an individual's risk of infection, thereby reducing the benefit of vaccinating. Second, peers can affect the perceived cost of vaccination through sharing information about vaccine safety or signaling social acceptance. Families may interpret high vaccination rates as evidence that vaccination is safe or socially expected. Third, peer vaccination can change the perceived consequences of remaining unvaccinated. In highly vaccinated settings, remaining unvaccinated may carry greater stigma, and illness-related absences may be more academically costly when fewer classmates are also absent. Because these channels operate in opposite directions, the net

effect of peer vaccination on individual take-up is theoretically ambiguous. Whether, how, and to what extent peer vaccination affects individual vaccination decisions is therefore an empirical question we aim to address in this paper.

Despite a large literature on vaccine hesitancy, causal evidence on the impact of peer vaccination in schools remains limited. Existing studies show that peer vaccination shapes individual take-up in other settings, but none has examined its effect on vaccine take-up in K–12 schools. Attendance matters not only as a proximal measure of illness but also because it is vital to academic success. Where vaccination is voluntary, then, understanding how students respond to their peers' vaccination is essential for determining when and how policymakers should intervene to minimize health risks in schools.

To be concrete, we leverage the age-based rollout of COVID vaccines together with rich student-level data. Vaccines first became available to school-age children for the 2021–22 school year, though vaccination was not required to attend school. Children ages 12 and older gained access before the school year began, while children ages 5 to 11 became eligible partway through the fall semester. This staggered rollout generated variation in peer access to vaccination at school start, which we use as an instrument for peer vaccination rates. Using linked student-level vaccination, attendance, demographic, and school records from New York City (NYC), we study sixth-, seventh-, and eighth-graders and estimate effects on individual vaccine take-up, attendance rates, and chronic absenteeism,[1] along with heterogeneity by race/ethnicity and gender.

Results indicate peer vaccination matters. A 10-percentage-point increase in peer vaccination raises a student's own take-up by 1.7 percentage points, increases the attendance rate

[1] Chronic absenteeism is a widely used measure of school accountability under the Federal Every Student Succeeds Act (ESSA) framework. In New York, as in most states, it is defined as missing 10 percent or more days of school.

by 0.7 percentage points, and reduces chronic absenteeism by 2.9 percentage points. Relative to baseline rates, these estimates imply a 2.5 percent increase in vaccine take-up and a 9 percent reduction in chronic absenteeism. The attendance effect is smaller relative to the high baseline attendance rate, but is equivalent to about an 8 percent reduction in absences. These magnitudes are meaningful: the 1.7-percentage-point take-up effect is roughly 40 to 60 percent of the 2.8 to 4.1-percentage-point increase in vaccination rates that Bald et al. (2026) find following state repeal of nonmedical exemptions from mandatory vaccination. And the attendance effect of a 0.7-percentage-point increase is roughly one-quarter the size of the average effect on attendance outcomes reported by Eklund et al. (2022) for academic interventions, such as tutoring.[2]

We also find evidence of heterogeneity by race/ethnicity, but no evidence of meaningful differences by gender. Vaccination take-up responses to peer vaccination are similar for Hispanic and Black students, and smaller for White and Asian students. A 10-percentage-point increase in peer vaccination raises take-up by roughly 2 percentage points for Hispanic and Black students, compared with about 1 percentage point for White students and less than half a percentage point for Asian students. Attendance and chronic absenteeism responses follow a related but distinct pattern, with Black students the most responsive group. The same increase raises attendance by about 0.7 percentage points for Hispanic and Asian students, about 1 percentage point for Black students, and about 0.6 percentage points for White students. It reduces chronic absenteeism by about 3 percentage points for Hispanic and Asian students, 4 percentage points for Black students, and 2 percentage points for White students.

[2] With a standard deviation of 0.103, the standardized effect (Hedges' g) of a 0.7-percentage-point increase in attendance rate is around 0.068. Eklund et al., 2022 estimate an average g of 0.25.

Taken together, these findings provide credible causal evidence that peer vaccination meaningfully shapes both individual vaccine decisions and school attendance. Although our empirical setting is the COVID vaccine rollout, the underlying mechanisms likely extend to vaccine take-up decisions for a broader set of diseases and contexts. Many school-based health decisions are voluntary or partially discretionary, and many communicable diseases spread through shared school environments. As routine childhood vaccination coverage declines, peer health behavior is becoming an increasingly important determinant of the school health environment. By linking peer vaccination to both take-up and attendance, this paper shows that voluntary vaccination decisions can generate spillovers not only in health behavior but also in schooling.

2. NYC COVID and Policy Context

NYC schools during the 2021–22 school year provide an especially useful setting for studying the impact of peer vaccination. During this period, NYC schools pushed for a return to normalcy (i.e., in-person instruction), while COVID continued to circulate widely. Indeed, between late December and early January, the city recorded its highest number of verified COVID cases (NYC DOHMH, n.d.). NYC schools differ widely in both demographic composition and built environment, generating variation in the COVID risk students faced at school and, consequently, in incentives to vaccinate.

The incentive to vaccinate varied across schools because citywide school reopening policies and mitigation strategies operated through school-specific conditions. The NYC Department of Education (NYCDOE) followed public-health guidance for reopening schools, including social distancing where possible, regular testing, sanitation procedures, mask requirements, and efforts to encourage vaccination (NYCDOE, 2021). But NYC school buildings

vary widely in layout, size, space, and utilization, which affects the practicality of strategies such as social distancing. Classroom space ranged from 20 to more than 60 square feet per pupil (see Quinn, Rothbart, Schwartz, and Elbel, "Absenteeism, Race and the Role of the School Environment"), and few schools had sufficient capacity for the recommended 6 feet of social distancing without using auxiliary spaces, such as auditoriums or cafeterias (NYC IBO, 2020). Student vaccination was voluntary, but several policies created direct incentives to vaccinate: vaccination was required for certain extracurricular activities, such as sports, and vaccinated students were exempt from quarantining when otherwise required. Schools also differed in how they ran information campaigns to encourage vaccination, offered incentive programs (e.g., gift card raffles), and hosted in-school vaccine clinics. Together, these differences meant that students faced different school-based risks and different private benefits and costs of vaccination. Thus, in aggregate, peer vaccination likely differed across schools.

Peer vaccination also differed across schools and grades for reasons outside incentives from school policies or building conditions: the age-based rollout of COVID vaccine eligibility. Eligibility was set federally as the FDA authorized vaccines for successive age groups. As shown in **Figure 1,** students aged 12 to 15 became eligible on May 10, 2021, before the 2021–22 school year began; students aged 5 to 11 followed on October 29, 2021, mid-fall semester (HHS, 2024). This age-12 threshold created large differences in peer eligibility across middle school grades at the start of the school year: most sixth-graders fell below it, eighth-graders were almost entirely above it, and seventh-graders were somewhere in between. Because NYC's school-entry cutoff falls on December 31 rather than at the start of the year, ages at the start of the year vary within grades, so same-age students could face very different peer environments depending on their

entering grade. Because NYC schools serve different grade spans, these age-based eligibility rules produced different schoolmate eligibility and, in turn, vaccination rates across schools.

Students faced a real risk of COVID infection, as evidenced by disrupted attendance patterns observed both nationally and in NYC. After the onset of the pandemic, attendance fell, and chronic absenteeism rose substantially, with pronounced disruptions for Black and Hispanic students (Gee et al., 2023; Dee, 2024; Mitsdarffer et al., n.d.). These racial disparities in absenteeism may partly reflect differences in school environments that shaped COVID risk, including peer vaccination rates. Consistent with this hypothesis, prior research found that racial disparities in absenteeism narrowed when controlling for school-level vaccination rates and space per pupil in NYC (see Quinn, Rothbart, Schwartz, and Elbel, "Absenteeism, Race and the Role of the School Environment"). The attendance disruptions make the peer environment consequential: peer vaccination may have shaped both students' incentives to vaccinate and the COVID-related risks they faced at school. Understanding peer vaccination matters because it may have shaped both the health risks students faced at school and the schooling disruptions that followed.

3. Literature Review

This paper builds on and contributes to three related literatures: determinants of vaccine take-up, peer effects in health and education, and the relationship between student health and absenteeism.

Determinants of vaccine take-up. Canonical economic models of vaccination emphasize the private costs of vaccination and expected infection risk as determinants of take-up (Brito et al., 1991; Geoffard & Philipson, 1997; Philipson, 2000). Empirically, prior work generally finds

that take-up is positively associated with local vaccination rates and case rates, as well as greater vaccine access (Romley, Goutam, and Sood, 2016; Hilverda & Vollmann, 2021). However, while prior work consistently finds that individuals respond to perceived private infection risk, they do not internalize how their choice affects others (Xiao et al., 2025). The vaccine hesitancy literature frames take-up as shaped not only by expected infection risk and costs, but also by trust, information, perceived safety, and cultural beliefs (Brumbaugh et al., 2025; Sacks & Sydnor, 2025). Consistent with normative and informational channels, vaccine take-up among conservatives is higher in more liberal than conservative areas (Dinero et al., 2026). Causal evidence also shows that vaccination decisions respond to personal risk, information, institutional rules, and costs, including reminder messages, mandates, exemption policies, and vaccine access costs (Nyathi et al., 2019; Milkman et al., 2022; Churchill & Henkhaus, 2023; Bald et al., 2026).

To our knowledge, this is the first study to use quasi-experimental variation in peer vaccine access to estimate the causal effect of schoolmate vaccination on own vaccine take-up in a K–12 setting. Prior work finds that vaccination increases take-up among other family members for flu and HPV (Miyazato et al., 2024; Humlum et al., 2024), and friends' flu vaccination increases take-up among college students (Rao et al., 2007). Miyazato et al. (2024) also find a positive spillover from neighborhood vaccination. However, Bouckaert et al. (2020) found that adults aged 65 and older who received the flu vaccine had a negative spillover on their adult children's vaccine take-up. These studies provide evidence that vaccination behavior can spill over within families, friendship networks, and neighborhoods, but they do not identify peer vaccination effects among schoolmates in K–12 settings.

Peer effects in health and education. A broad literature shows that students are affected by their schoolmates' behaviors and characteristics. For health outcomes, prior work finds that schoolmates influence risky behaviors, such as drug use, as well as health measures such as weight (Card & Giuliano, 2013; Tan & Zapryanova, 2022; Asirvatham et al., 2019; Presler, 2022). Most directly relevant, Freedman et al. (2026) find that child vaccination reduces illness among household members but find no evidence of spillovers among school peers. Their study differs from ours because it does not directly observe school assignments and uses hospitalizations rather than absences as the student outcome of interest. For education outcomes, there is a large literature on peer effects on attendance and test scores (Gottfried, 2014). An important takeaway from the peer effect literature is that peer effects are generally more credible and often larger when peers are defined more proximally (Hoxby, 2000; Fruehwirth, 2013; Briole, 2021). Classmates or grademates are likely to be more relevant peer groups than all schoolmates, especially for outcomes shaped by daily interaction, shared exposure, and classroom norms.

Student health and absenteeism. Absenteeism is a proximal measure of student health and consequential in its own right: absences disrupt learning, and attendance strongly predicts academic performance and long-run success. Public health experts have used school absenteeism for disease surveillance and early outbreak detection for decades (Besculides et al., 2005; Dailey et al., 2007; Schmidt et al., 2010; de Korne et al., 2026). After all, absenteeism has been closely linked to student health, with prior work documenting associations between absence and illness and poor physical and mental health (Gottfried & Gee, 2017; Kim et al., 2020; Malika et al., 2021; Hendron & Kearney, 2016; Askeland et al., 2020; Allison et al., 2019). Most relevant to our study, a body of work has shown that vaccination improves school attendance. Both own

vaccination and peer vaccination are associated with higher attendance (Nettleman et al., 2001; Wiggs-Stayner et al., 2006; King et al., 2012; Pannaraj et al., 2014). Our study adds to this literature by providing the first evidence of the impact of grademate vaccination on attendance.

Finally, absenteeism is strongly predictive of academic success. Absence accrual is associated with poorer end-of-year outcomes, such as lower test scores and grades (Gottfried, 2014; London et al., 2016; Liu et al., 2021; Keppens, 2023). Absences are also associated with negative longer-term academic and behavioral outcomes, including dropping out of school, drug use, and future unemployment (Alexander et al., 1997; Hallfors et al., 2002; Rumberger & Rotermund, 2012; Smerillo et al., 2018; Ansari et al., 2020). Beyond their importance as measures of academic success, end-of-year attendance measures (i.e., chronic absenteeism) are key accountability metrics under the Every Student Succeeds Act (ESSA) and thus influence schools' strategic decisions.

4. A Simple Model of Vaccination Take-up

To fix ideas, we develop a simple expected-utility model linking the individual vaccination decision to vaccine take-up among peers. Individuals (students or parents for their children) choose vaccination when the expected utility of vaccination exceeds the expected utility of remaining unvaccinated, net of costs. Peer vaccination can affect several aspects of the vaccination decision: the expected risk of getting COVID, the consequences of becoming infected, and the perceived cost of vaccination. These changes can push take-up in different directions. For example, more vaccinated peers may lower the risk of infection and therefore reduce the private return to vaccination. However, they can also lower the perceived cost of vaccination by signaling vaccine safety or reducing information frictions. Thus, the net effect of peer vaccination on own vaccination is theoretically ambiguous.

The following model formalizes these competing channels. Let v be a "vaccinated" indicator equal to one if the student is vaccinated, and θ be the percentage of peers who are vaccinated. Utility depends on COVID status as well as peer vaccination rates, since a student's COVID status can affect the consequences of peer vaccination. For example, getting sick in a high-vaccination environment may carry greater stigma. Let $U(1;\theta)$ and $U(0;\theta)$ denote utility if the student has had COVID and if the student has not had COVID, respectively, and having COVID decreases utility such that $U(0;\theta) > U(1;\theta)$. We define $p(v;\theta)$ as the probability of getting COVID, which depends upon vaccination status – both vaccinated and unvaccinated individuals may get COVID – as vaccination reduces the probability of getting COVID, or a case with severe symptoms, thus $p(v=1;\theta) < p(v=0;\theta)$.[3] The probability of getting COVID also depends on θ as increased vaccine coverage reduces the chance a student comes into contact with an infected peer.

Then the expected utility of vaccination is

$$E[U|\, v=1] = p(1;\theta)U(1;\theta) + \big(1-p(1;\theta)\big)U(0;\theta).$$

Expected utility without vaccination is

$$E[U|\, v=0] = p(0;\theta)U(1;\theta) + \big(1-p(0;\,\theta)\big)U(0;\theta).$$

and the expected net benefit of vaccination:

$$ENB(\theta) = E[U|v=1] - E[U|\, v=0] - c(\theta),$$

where $c(\theta)$ is the cost of vaccination, including monetary costs, side effects, and other potential costs, which depend upon θ. If $ENB(\theta) > 0$, families choose vaccination.

Rearranging yields:

[3] Unlike other vaccination models, we do not assume vaccination perfectly eliminates the risk of infection as in Brito et al. (1991).

$$ENB(\theta) = \Delta p(\theta)\Delta U(\theta) - c(\theta),$$

where $\Delta p(\theta) = p(v = 0; \theta) - p(v = 1; \theta)$ is the reduction in the probability of getting COVID due to own vaccination, and $\Delta U(\theta) = U(0; \theta) - U(1; \theta)$ is the utility loss from getting COVID**.** As vaccination reduces the chance of getting COVID and having COVID lowers utility, it follows that $\Delta p(\theta) > 0$ and $\Delta U(\theta) > 0$. Notice that ENB is increasing in $\Delta p(\theta)$, and $\Delta U(\theta)$, but decreasing with $c(\theta)$. Peer vaccination can therefore affect the expected net benefit of vaccination and, consequently, vaccination decisions, by changing the infection-probability reduction from own vaccination, the utility loss from infection, or the cost of vaccination.

The effect of peer vaccination on own take-up is theoretically ambiguous. Differentiating the expected net benefit with respect to θ gives:

$$\frac{\partial ENB(\theta)}{\partial \theta} = \underbrace{\Delta p'(\theta)}_{-}\underbrace{\Delta U(\theta)}_{+} + \underbrace{\Delta p(\theta)}_{+}\underbrace{\Delta U'(\theta)}_{+/-\,?} - \underbrace{c'(\theta)}_{-}.$$

This expression decomposes the effect of peer vaccination on own take-up into three channels: an infection-probability channel, $\Delta p'(\theta)\Delta U(\theta)$; a utility-loss channel, $\Delta p(\theta)\Delta U'(\theta)$; and a cost channel, $-c'(\theta)$. The infection-probability channel is negative because peer vaccination lowers infection risk more for the unvaccinated than for the vaccinated, $\Delta p'(\theta) < 0$, as vaccinated students are already partially protected. By contrast, the cost channel is positive as peer vaccination lowers the perceived cost of vaccination by reducing information costs, perceived side-effect risks, and social stigma around vaccination, so that $c'(\theta) < 0$. The utility-loss channel can work in either direction because peer vaccination can make getting COVID less costly in some ways and more costly in others, so $\Delta U'(\theta)$ is ambiguous.[4] Thus, peer vaccination can either increase or decrease own take-up.

[4] Peer vaccination may lower the loss from infection by reducing concern about transmitting COVID to susceptible peers. It may also raise the loss if, when most peers are vaccinated and attending school, an infected student misses

The relative strength of these competing effects may vary over the distribution of peer vaccination, implying a nonlinear relationship between peer vaccination and own take-up. As an example, there may be a critical threshold of vaccination that provides "herd immunity", at which transmission begins to fall sharply. The existence of such thresholds implies that $\Delta p(\theta)$ need not decline linearly with θ. Far below the herd-immunity threshold, marginal increases in θ likely do little to reduce transmission, so $\Delta p'(\theta)$ remains small, and $\Delta p(\theta)$ will remain quite large. Near the threshold, small increases in θ can sharply reduce infection risk for unvaccinated students, causing $\Delta p(\theta)$ to fall quickly and $\Delta p'(\theta)$ to become more negative. Because the infection-probability channel depends on $\Delta p'(\theta)$, while the utility-loss channel depends on $\Delta p(\theta)$, herd immunity implies the relative strength of these channels will vary over θ. The infection-probability channel will be strongest near the threshold. In contrast, the utility-loss channel will be strongest where the infection-probability reduction from vaccination remains large.

The model is intentionally simplified and provides a partial-equilibrium framework. It treats the peer vaccination rate at school start as given when a family makes its vaccination decision, rather than modeling vaccination choices as a jointly determined game. It therefore does not capture how one family's response may feed back into other families' decisions or determine the resulting equilibrium vaccination rate. This simplification suits our setting particularly well. Because vaccine eligibility was staggered by age, many peers had already been vaccinated by school start, and the empirical design uses eligibility timing to isolate exogenous variation in this beginning-of-year peer vaccination rate. For students who were not yet eligible

more instruction relative to classmates, faces greater stigma, or imposes larger social costs by disrupting a mostly protected environment.

at school start, the share of peers vaccinated at that point could not respond to the student's subsequent vaccination decision.

The model also combines monetary, access, and perceived side-effect costs into a single linear reduced-form cost term $c(\theta)$ rather than including each cost directly in the utility function. A fuller model could allow these costs to enter utility separately and nonlinearly and could distinguish between the effects of vaccination on the probability of infection and on the severity of illness conditional on infection.[5] These simplifications limit the model's equilibrium implications but not its usefulness for the empirical analysis. The model identifies competing channels through which peer vaccination can affect own take-up, demonstrates that the net effect is theoretically ambiguous, and predicts that the effect may vary across the peer-vaccination distribution. Correspondingly, the empirical design estimates the partial-equilibrium effects of beginning-of-year peer vaccination on subsequent take-up and attendance under the vaccination costs and institutional conditions prevailing during the study period.

5. Data and Measures

We use data from the Student Population Health Registry (SPHR), a comprehensive longitudinal database linking individual-level administrative records for NYC public school students to multiple health data sources**.** Education data include student sociodemographic characteristics, school enrollment, and daily attendance from the NYC Department of Education (NYCDOE). Vaccination records from the Citywide Immunization Registry and the NYC Department of Health and Mental Hygiene (DOHMH) include unique student identifiers to link school records and the dates each student received a dose of the COVID vaccine.

[5] Allowing vaccination to affect the severity of illness conditional on infection would add another channel without changing the model's central intuition. Equivalently, the two health states could be interpreted as severe symptoms and no severe symptoms, rather than infection and no infection.

The data also include demographic and program participation characteristics. Demographic characteristics include race and ethnicity ($Asian$, $Black$, $Hispanic$, $White$, $Other$[6]), sex ($Female$), and date of birth. Program participation variables include English learner status (EverELL), students with disabilities (SWD), and Medicaid participation (Medicaid). *EverELL* indicates that the student has received language support services, *SWD* indicates the student had an individualized education plan, and Medicaid participation serves as our measure of economic disadvantage. We define age in months as of the start of the school year.

Our analytic sample includes traditional public-school students[7] enrolled in grades 6, 7, or 8 during the 2021–22 school year. We focus on grades 6–8 because students in these grades were concentrated around the age-12 vaccine-eligibility cutoff at school start. The sample does not include charter, full-time special education, or alternative schools.[8] To ensure that peer measures are defined within mixed-gender school-grade environments, we restrict the sample to coeducational schools in which each school-grade cell includes at least five male and five female students. The sample includes 170,837 students attending 467 public schools.

We construct two grademate peer measures: peer vaccination, the treatment of interest, and peer eligibility, the instrument. $EligRate_{-i,g,s}$ is the leave-one-out school-grade eligibility rate, measured from 0 to 100. It equals 100 times the number of students other than i in grade g at school s who were age 12 or older on September 13, 2021, divided by the total number of students other than i enrolled in the same school-grade. $VaxRate_{-i,g,s}$ is defined analogously,

[6] Other includes students of Native American, multiracial, or unknown race/ethnicity.
[7] A small fraction of students was excluded because they switched schools in the middle of the school year or were more than two years overage or underage for grade.
[8] NYC's citywide alternative schools district serves students in nontraditional educational settings, including students on Superintendent's Suspension, court-involved youth, and students in transfer or re-engagement programs.

using the number of same-grade peers who had received at least one COVID vaccine dose by school start.

We use alternative peer measures to assess whether the estimated effects depend on peer-group definition or exposure timing. First, we create school-level analogues to our treatment and instrument, $SchEligRate_{-i,s}$ and $SchVaxRate_{-i,s}$. These school-level measures allow us to compare grademate exposure with a broader, less proximate schoolmate measure based on differences in the grades schools serve. Second, because school start is a natural but not uniquely correct date for measuring peer vaccination exposure, we measure vaccination rates at later points in the school year. These dates include when younger students became eligible (October 29, 2021), when school vaccination rates were announced (February 22, 2022), and the end of the school year (May 23, 2022). We denote these measures as $VaxRate^{t}_{-i,g,s}$ where *t* indexes the measurement date.

We measure three student outcomes: own vaccination status, attendance rate, and chronic absenteeism. Own vaccination status, $VaxST_{i,g,s}$, equals one if student i received at least one COVID vaccine dose by May 23, 2022, the end of the school year. Attendance rate, $AttRate_{i,g,s}$, equals the percentage of enrolled school days during the academic year that student *i* was present. Chronic absenteeism, $Chronic_{i,g,s}$, equals one if $AttRate_{i,g,s}$ is at or below 90 percent.

The sample is large and demographically diverse, allowing us to examine heterogeneity in the effects of peer vaccination. As shown in **Table 1**, **r**oughly 43 percent of students are Hispanic, 20 percent are Black, 19 percent are Asian, and 16 percent are White. Even the smallest racial group, White students, includes 27,922 observations. Three-quarters of the sample are low income, as indicated by participation in Medicaid. Student characteristics differ sharply across racial groups. Medicaid participation is substantially higher among Hispanic, Black, and

Asian students at 84, 81, and 78 percent, respectively, compared with 48 percent among White students. The SWD rate is highest for Black and Hispanic students, at 26 percent, compared with 17 percent among White students and 8 percent among Asian students.

Table 1 also shows large average differences across racial groups in the outcomes and treatment, but not the proposed instrument**.** Asian students have both the highest end-of-year vaccination rate, 86 percent, and the lowest chronic absenteeism rate, 14 percent. White students, by contrast, have the lowest vaccination rate, 53 percent, but substantially lower chronic absenteeism than Black or Hispanic students. Black and Hispanic students have vaccination rates of 57 and 68 percent, respectively, but chronic absenteeism rates of 40 and 38 percent. Peer vaccination exposure also varies by race and ethnicity, ranging from 28 percent among Black students to 40 percent among Asian students. By contrast, peer eligibility is much more similar across groups, ranging from about 61 to 65 percent. Thus, reassuringly, while the treatment and student outcomes differ sharply across racial and ethnic groups, the proposed instrument is relatively consistent.

Figures 2 and 3 show how the age-based vaccine eligibility rollout generated variation in peer vaccination. **Figure 2** shows sharp differences in grademate eligibility at school start: sixth-grade peer groups were mostly ineligible, seventh-grade peer groups had high but variable eligibility, and eighth-grade peer groups were almost universally eligible. Eligibility made vaccination possible, but it did not mean a student had received a dose. Thus, higher eligibility shifts vaccination rates upward without mechanically determining them. As shown in **Figure 3**, sixth-grade peer vaccination was concentrated near zero, while seventh- and eighth-grade peer groups had substantially higher and more dispersed vaccination rates.

6. Methodology

Estimating the effect of peer vaccination on student outcomes presents two threats to identification common in the peer effects literature: correlated effects and the reflection problem (Manski, 1993). Correlated effects arise when students in the same peer group behave similarly, not because they influence one another, but because they are alike or face a common environment. In this setting, students nonrandomly sort into schools and neighborhoods with peers like them (Hoxby, 2000) and may share unobserved characteristics such as risk tolerance or transportation access that affect both peer vaccination and own take-up or attendance. The reflection problem arises because individual and peer behavior may be jointly determined: students may respond to grademates' vaccination decisions, while grademate vaccination is itself generated by vaccination decisions within the peer group.

To address potential correlated effects, we include school fixed effects and flexible controls for student age. School fixed effects capture time-invariant school characteristics, and our key coefficient is identified by comparisons of students within schools rather than across. More specifically, we compare students in different grades within the same school, holding fixed school-wide factors such as neighborhood context, vaccine access, school leadership, mitigation practices, and local vaccination norms. Age-in-month[9] fixed effects are especially important because eligibility is age-based, and age is related to grade placement and attendance. By comparing students of the same age, we compare students who have had the same amount of time to get vaccinated and have similar attributes that shape attendance behavior.[10]

[9] Our preferred specification controls flexibly for age using age-in-month fixed effects. Results are robust to alternative age controls.

[10] In NYC, holding a child back from starting kindergarten to give them an extra year to mature ("red-shirting") is not allowed, so we are less concerned about sorting across grades along unobservable characteristics conditional on age in months.

To address the potential reflection problem, we instrument leave-one-out grademate vaccination with leave-one-out grademate eligibility. Grademate eligibility provides plausibly exogenous variation in peer vaccination because it depends on federally established age thresholds and students' dates of birth, rather than vaccination choices or attendance outcomes of students, families, or schools. Leave-one-out peer measures remove each student's own eligibility and vaccination status from the peer measures, ensuring that peer eligibility and vaccination are not mechanically linked from the student's own values.

Formally, we estimate the following two-stage least squares model. The first stage is:

$$VaxRate_{-i,gs} = \alpha' + \mu EligRate_{-i,g,s} + \delta X_{i,g,s} + \phi_s + \lambda_{a(i)} + v_{i,g,s} \quad (1)$$

The second stage is:

$$\mathrm{Y_{i,g,s}} = \alpha + \beta \widehat{VaxRate}_{-i,g,s} + \gamma X_{i,g,s} + \phi_s + \lambda_{a(i)} + \varepsilon_{i,g,s} \quad (2)$$

$VaxRate_{-i,g,s}$ is the leave-one-out grademate vaccination rate, and $EligRate_{-i,g,s}$ is the corresponding leave-one-out grademate eligibility rate, both measured at school start and scaled from 0 to 100. $\mathrm{Y_{i,g,s}}$ denotes one of the three student outcomes: own vaccination status, attendance rate, or chronic absenteeism. $X_{i,g,s}$ includes student race/ethnicity, sex, Medicaid participation, SWD, and EverELL status. The model includes school fixed effects, ϕ_s, and age-in-month fixed effects, $\lambda_{a(i)}$, where $a(i)$ is student i's age in months at school start. Standard errors are clustered by school-grade. The coefficient of interest is β which gives the effect of a one-percentage-point increase in grademate vaccination on student outcomes. Note that the β estimates represents a partial-equilibrium effects of beginning-of-year peer vaccination on a student's subsequent vaccination take-up and attendance in the context of NYC in 2021-22. The estimates do not incorporate feedback from the student's response to the subsequent choices of other students or identify the equilibrium effect of a systemwide change in vaccination policy.

For the instrument to identify a causal effect it must satisfy two conditions. First, the instrument must be relevant: grademate eligibility strongly predicts grademate vaccination. We assess this condition in the first stage with the relationship between $EligRate_{-i,g,s}$ and $VaxRate_{-i,g,s}$, and the associated first-stage F-statistic as a weak-instrument diagnostic. In this context, eligibility should be strongly relevant because students who were not yet age-eligible at the start of the school year had limited access to vaccination. Second, the instrument must satisfy the exclusion restriction. The exclusion restriction requires that grademate eligibility affect student outcomes only through grademate vaccination, and not through peer age composition, grade-level shocks, or other school-grade characteristics. We include student age-in-month fixed effects to mitigate potential confounding through own age, and school fixed effects to absorb fixed differences in school environments.

We also estimate OLS and reduced-form models as empirical benchmarks. The OLS model relates student outcomes directly to grademate vaccination, using the same controls and fixed effects as the IV specification:

$$Y_{igs} = a + \beta VaxRate_{-i,g,s} + \gamma X_{igs} + \phi_s + \lambda_{a(i)} + \epsilon_{igs} \quad (3)$$

The reduced-form model is analogous but replaces $VaxRate_{-i,g,s}$ with $EligRate_{-i,g,s}$. The OLS estimates provide a descriptive benchmark for the endogenous relationship between grademate vaccination and student outcomes, while the reduced-form estimates show how the instrument itself relates to the outcomes.

Finally, we estimate three alternative specifications. First, we replace grademate vaccination and eligibility with schoolmate measures. Because schoolmate measures are defined at the school level, these models omit school fixed effects. These models leverage eligibility variation across schools from differences in grades served and schoolwide age compositions.

This specification allows us to compare the main grademate estimates with estimates based on a broader, less proximate peer group. Second, we examine nonlinearities by estimating quadratic and cubic specifications of grademate vaccination, using corresponding powers of grademate eligibility as instruments. These specifications allow the marginal relationship between peer vaccination and student outcomes to vary over the distribution of grademate vaccination. Third, we estimate models using alternative dates to define grademate vaccination rather than measuring vaccination only at the start of school. These dates include when 5- to 11-year-olds became eligible (October 29, 2021), when school vaccination rates were publicly announced (February 22, 2022), and the end of the school year (May 23, 2022).

7. Results

Peer eligibility is a highly relevant instrument for peer vaccination. Column (1) of **Table 2** shows that peer eligibility strongly predicts peer vaccination. Specifically, a one-percentage-point increase in grademate eligibility increases the grademate vaccination rate by 0.561 percentage points. The first-stage F-statistic is 5,561, far above conventional weak-instrument thresholds. Columns (2) through (4) report the reduced-form relationships between grademate eligibility and student outcomes. Higher grademate eligibility is associated with higher own vaccination, higher attendance, and lower chronic absenteeism. These reduced-form estimates show that the same eligibility variation that drives grademate vaccination is also associated with student outcomes.

Greater peer vaccination increases own vaccine take-up and improves attendance outcomes. **Table 3** reports OLS estimates as a benchmark in Panel A and 2SLS estimates in Panel B. The 2SLS estimates imply that a 10-percentage-point increase in peer vaccination increases own vaccine take-up by 1.7 percentage points, raises the attendance rate by 0.7

percentage points, and reduces chronic absenteeism by 2.9 percentage points. Across outcomes, the OLS estimates have the same signs but are substantially smaller than the 2SLS estimates. For example, the OLS estimate for own vaccine take-up is 0.2 percentage points, nearly an order of magnitude smaller than the corresponding 2SLS estimate.

The effects of peer vaccination differ by race and ethnicity, but not by gender. The first stage remains strong in both the race/ethnicity and gender heterogeneity models; Appendix **Tables A1** and **2.A2** report the corresponding first-stage estimates**.** As shown in **Table 4,** White and Asian students have smaller own-vaccination responses to peer vaccination than Hispanic students, the omitted group, while Black students respond similarly. A 10-percentage-point increase in peer vaccination increases own take-up by 2.2 percentage points for Hispanic students and 2.4 percentage points for Black students, compared with 1.3 percentage points for White students and less than 1 percentage point for Asian students. The attendance effects show a broadly similar pattern: Black students experience larger improvements than Hispanic students, while White students experience smaller improvements. For chronic absenteeism, a 10-percentage-point increase in peer vaccination reduces chronic absenteeism by 3.9, 3.0, 2.6, and 2.3 percentage points for Black, Hispanic, Asian, and White students, respectively. As shown in **Table 5**, the gender interactions are not statistically significant for any outcome.

The estimated effects are smaller for the broader schoolmate peer groups. Compared with the grademate models, all estimated effects are smaller in the schoolmate models. Schoolmate eligibility is a strong instrument for schoolmate vaccination (**Table A3**). However, as shown in **Table 6,** a 10-percentage-point increase in schoolmate vaccination increases own vaccine take-up by 1.3 percentage points (around 19% smaller than the grademate effect). It has no

statistically significant effect on attendance rates or chronic absenteeism. The results are robust to the inclusion of either age fixed effects or grade fixed effects.

The nonlinear specifications suggest that the effect of grademate vaccination varies over the vaccination distribution**.** The quadratic specification remains strong, with an F-statistic of 128, while the cubic specification is weaker with a first-stage F of 12 (**Table A4**). As shown in **Figure 4**, the marginal effect of grademate vaccination on own take-up is negative at very low vaccination rates, positive through the middle of the distribution, and negative again above roughly 60 percent. As shown in **Figures 5 and 2.6**, the attendance and chronic absenteeism estimates follow a similar pattern: the implied marginal effects are most beneficial in the middle of the distribution and become less favorable at very low and high levels of grademate vaccination. This pattern is broadly consistent with the conceptual framework.

Alternative Vaccination Rate Dates

Peer eligibility at school start remains a strong instrument for grademate vaccination rates measured later in the school year. As shown in **Appendix Table A6**, the first-stage F-statistic remains above 1,000 for each vaccination-rate date, far above conventional weak-instrument thresholds. The first stage is strongest for the October vaccination measure, when most students had become eligible, but remains strong for the February and May measures as well.

Estimates using later vaccination-rate measures are substantially larger than estimates using school-start vaccination, but this partly reflects a mechanical feature of the IV scaling**.** The IV estimate divides the eligibility-outcome relationship by the first-stage relationship between school-start eligibility and the vaccination measure. Because vaccination is measured later in the

year, initially ineligible students have more time to become eligible and be vaccinated, weakening the relationship between school-start eligibility and measured peer vaccination. Thus, a smaller first stage can mechanically translate a similar reduced-form relationship into a larger IV estimate. As shown in Appendix **Table A7**, a 10-percentage-point increase in grademate vaccination increases own vaccine take-up by 1.7 and 1.5 percentage points using the September and October measures, compared with 5.7 and 6.5 percentage points using the February and May measures. The attendance outcomes follow the same pattern: the estimated reduction in chronic absenteeism is about 3 percentage points with September or October vaccination, but about 10 to 11 percentage points with later-year measures. These later-date estimates are therefore useful for comparison with more cumulative peer-vaccination measures, but they should not be interpreted as the same school-start peer-vaccination effect.

8. Discussion and Conclusion

Vaccination decisions are often treated as individual choices, but they are made in shared social and institutional environments. In schools, peers' vaccination behavior may shape family perceptions of transmission risk, vaccine safety, local norms, and the consequences of infection. This paper shows that peer vaccination influences individual vaccination decisions. We also show that peer vaccination affects attendance outcomes, suggesting that voluntary vaccination behavior can generate spillovers in both health behavior and schooling.

The impact of peer vaccination on vaccine take-up provides evidence against a simple free-riding interpretation. Higher peer vaccination could reduce own take-up by lowering the private infection-risk benefit of vaccination. However, on average, we find the opposite. A 10-percentage-point increase in grademate vaccination increased own vaccine take-up by 1.7 percentage points. This does not imply the absence of free-riding. Rather, other channels,

including the cost and utility-loss channels in our framework, appear to have dominated the infection-probability channel on average.

The nonlinear estimates provide suggestive evidence that the effect of peer vaccination varies over the peer-vaccination distribution. At very low and very high levels of peer vaccination, the estimated marginal effect of peer vaccination on own take-up is negative, whereas the effect is positive through the middle of the distribution. This pattern is broadly consistent with the conceptual framework: when peer vaccination is very low, marginal increases may be insufficient to change the perceived school health environment meaningfully; when peer vaccination is very high, the private benefit of own vaccination may fall as additional protection becomes less valuable. Thus, the nonlinear results suggest that average effects may mask meaningful variation across peer environments.

The attendance results suggest that peer vaccination may generate downstream effects on schooling outcomes, either by increasing own vaccination, reducing exposure to infection, or reducing classroom disruption from peer absences. In the main 2SLS specification, a 10-percentage-point increase in peer vaccination at the start of the school year increases attendance by 0.7 percentage points and reduces chronic absenteeism by 2.9 percentage points. In the nonlinear models, the marginal peer effects on the attendance outcomes closely track the marginal effects on own vaccine take-up. This pattern is consistent with own vaccination being an important channel, though we cannot separately identify the mechanisms linking peer vaccination to attendance.

The comparison between gradeмate and schoolmate peer groups is consistent with the story that peer effects operated through relatively proximate social and educational environments. The schoolmate estimates are smaller than the gradeмate estimates and are not

statistically significant for attendance outcomes. However, the own-vaccination estimate remains similar in magnitude: about 20 percent smaller than the grademate estimate. Because the two models rely on different identifying variation, this consistency supports the robustness of the own-take-up result. By contrast, the weaker estimates of schoolmate attendance suggest that the downstream attendance effects are more sensitive to how the relevant peer environment is defined.

Within our setting, schools had COVID mitigation strategies in place. For example, universal masking was required through March 7, 2022. These strategies were designed to lower infection risk at school, which is directly related to both vaccination incentives and school absences. As a result, the estimated effects of peer vaccination may be attenuated relative to a setting with fewer mitigation policies, because the infection risk that peer vaccination could reduce was already partly reduced by masking and other school-based precautions. Lower infection risk reduces both the private incentive to vaccinate and the likelihood of illness-related absences. Given the meaningful effect sizes, we find that even in this lower-risk environment, the results reinforce the importance of considering spillovers when vaccination is voluntary.

For policymakers, the central lesson is that interventions shaping vaccine take-up may affect not only the students they directly reach, but also their peers. On average, this peer response acts as a multiplier; however, the suggestive nonlinear evidence indicates that the multiplier may weaken or reverse where take-up is already high. The total effect of a vaccination intervention may therefore depend on existing coverage. For vaccines such as seasonal influenza, the direction and magnitude of these peer responses will also likely depend on the vaccine's costs, effectiveness, and perceived disease risk. Evaluations that consider only directly treated students may consequently miss important peer responses.

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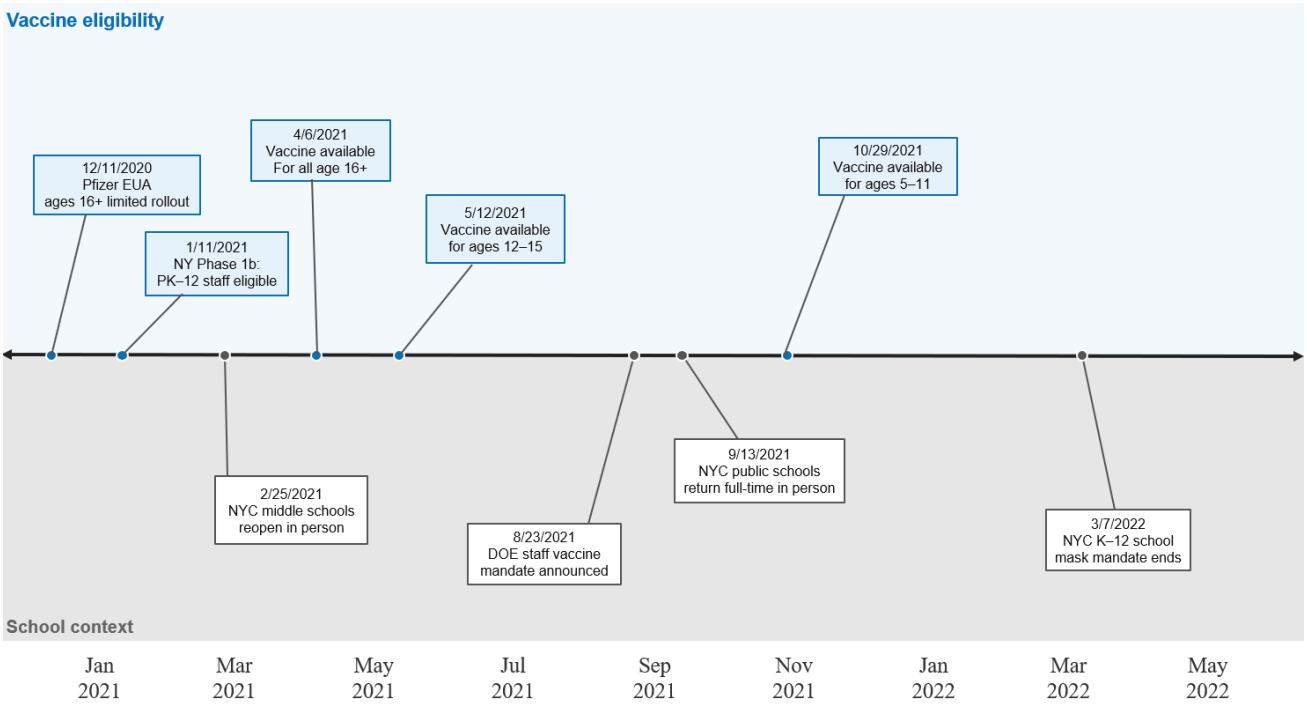
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Figure 1: NYC COVID-19 Vaccine Eligibility Timeline:

Key school-age vaccine eligibility dates, with selected NYC public-school context



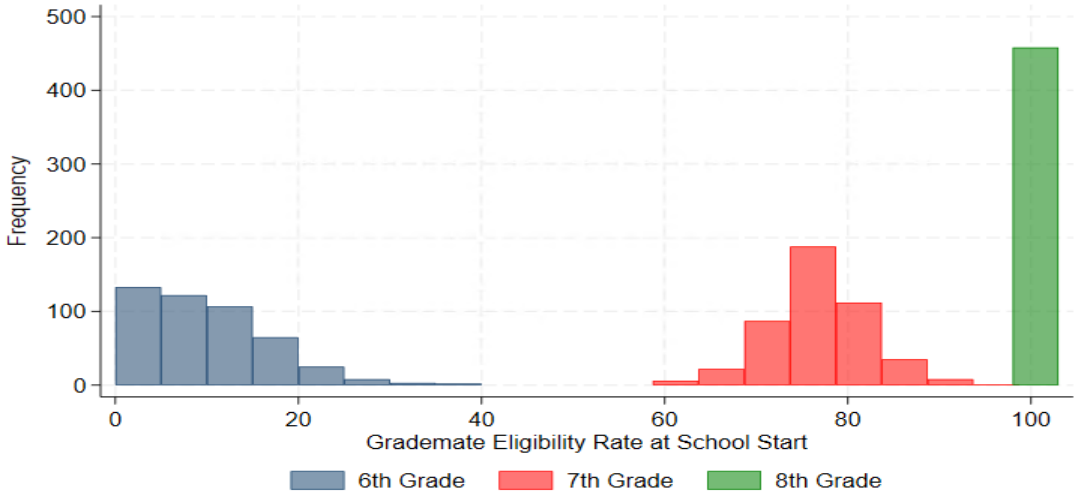
Note: Figure emphasizes vaccine eligibility rather than the full pandemic policy timeline. Eligibility dates reflect FDA authorizations and CDC recommendations. Elementary schools reopened to in-person instruction in November of 2020.

Table 1: Means, Key Variables, by Race/ethnicity

	All	**Asian**	**Black**	**Hispanic**	**White**
	(1)	(2)	(3)	(4)	(5)
Outcomes					
VaxST	0.67	0.86	0.57	0.68	0.53
AttRate	91.21	95.20	89.28	89.76	92.49
Chronic	0.31	0.14	0.40	0.38	0.24
Peers					
VaxRate	33.4	39.71	28.06	32.84	33.64
EligRate	62.56	62.13	64.78	62.61	60.68
Sociodemographic					
Female	0.49	0.48	0.50	0.49	0.48
SWD	0.21	0.08	0.26	0.26	0.17
Ever ELL	0.31	0.48	0.05	0.41	0.21
Medicaid	0.75	0.78	0.81	0.84	0.48
Age (Months)	147.80	147.40	148.57	147.96	146.99
N (Students)	170,837	32,622	33,129	72,690	27,922
N (%)	100%	19%	20%	43%	16%

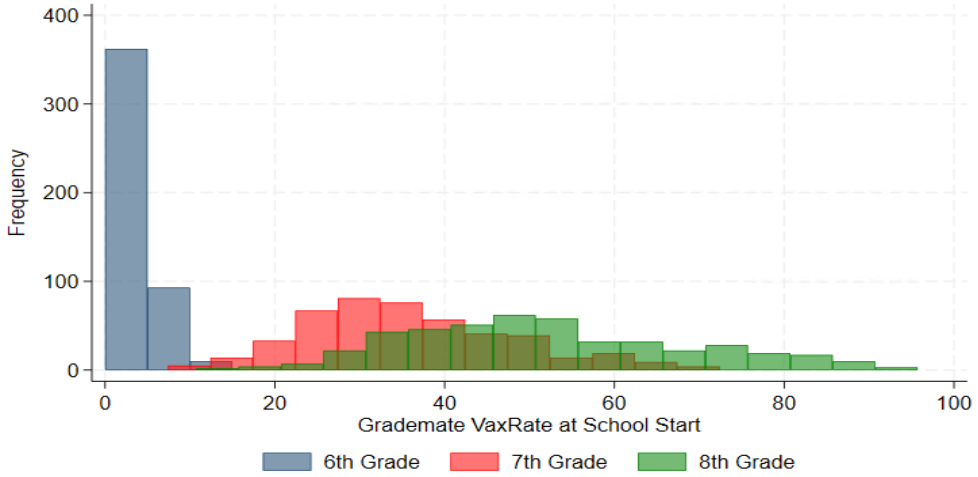
Note: Sample includes students enrolled in grades 6–8 in traditional, coeducational New York City public schools during the 2021–22 school year. VaxST is an indicator equal to one if the student received at least one COVID vaccine dose by May 23, 2022. AttRate is the percentage of enrolled school days the student was present. Chronic is an indicator equal to one if the student's attendance rate was 90 percent or lower. VaxRate is the leave-one-out grademate vaccination rate at school start, measured in percentage points. EligRate is the leave-one-out grademate share age 12 or older on September 13, 2021, measured in percentage points.

Figure 2: Distribution of Grademate Eligibility Rates at School Start, by Grade



Note: Figure shows the distribution of leave-one-out grademate eligibility rates at school start, by grade. Eligibility is defined as being age 12 or older on September 13, 2021. Eligibility rates are measured in percentage points.

Figure 3: Distribution of Grademate Vaccination Rates at School Start, by Grade



Note: Figure shows the distribution of leave-one-out grademate vaccination rates at school start, by grade. Vaccination is defined as having received at least one COVID vaccine dose by September 13, 2021. Vaccination rates are measured in percentage points.

Table 2: IV First-Stage and Reduced-Form Estimates

	VaxRate	**VaxST**	**AttRate**	**Chronic**
	(1)	(2)	(3)	(4)
EligRate	0.561***	0.0009***	0.039***	-0.0016***
	(0.008)	(0.0001)	(0.002)	(0.0001)
$\bar{y}$	33.4	0.6701	91.206	0.3125
R^2	0.93	0.12	0.16	0.13
N (Students)	170,837	170,837	170,837	170,837
First Stage F	5,561			

Note: Column 1 reports the first-stage relationship between leave-one-out grademate eligibility and leave-one-out grademate vaccination at school start. Columns 2–4 report reduced-form estimates of the relationship between grademate eligibility and student outcomes. Peer vaccination, peer eligibility, and attendance are measured in percentage points. Own vaccination and chronic absenteeism are indicators. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table 3: OLS and IV Estimates of Peer Vaccination Effects

	VaxST	AttRate	Chronic
	(1)	(2)	(3)
Panel A. OLS			
VaxRate	0.0002**	0.0444***	-0.0018***
	(0.0001)	(0.0025)	(0.0001)
Panel B. IV			
VaxRate	0.0017***	0.0700***	-0.0029***
	(0.0001)	(0.0034)	(0.0002)
$\bar{y}$	0.6701	91.2055	0.3125
N (Students)	170,837	170,837	170,837

Note: Panel A reports OLS estimates of the relationship between leave-one-out grademate vaccination and student outcomes. Panel B reports 2SLS estimates instrumenting leave-one-out grademate vaccination with leave-one-out grademate eligibility at school start. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table 4: IV Estimates of Peer Vaccination Effects by Race/Ethnicity

	VaxST	**AttRate**	**Chronic**
	(1)	(2)	(3)
VaxRate	0.0022***	0.0693***	-0.0030***
	(0.0002)	(0.0038)	(0.0002)
x Asian	-0.0019***	-0.0038	0.0004**
	(0.0002)	(0.0040)	(0.0002)
x Black	0.0002	0.0252***	-0.0009***
	(0.0002)	(0.0047)	(0.0002)
x White	-0.0009***	-0.0119***	0.0007***
	(0.0003)	(0.0035)	(0.0002)
x Other	-0.0010**	-0.0074	-0.0005*
	(0.0004)	(0.0057)	(0.0003)
$\bar{y}$	0.6701	91.2055	0.3125

Note: Table reports 2SLS estimates allowing the effect of leave-one-out grademate vaccination to vary by race/ethnicity. The omitted race/ethnicity category is Hispanic. The main coefficient gives the estimated effect for Hispanic students; interaction terms give differences relative to Hispanic students. Peer vaccination, peer eligibility, and attendance are measured in percentage points. Own vaccination and chronic absenteeism are indicators. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table 5: IV Estimates of Peer Vaccination Effects by Gender

	VaxST	**AttRate**	**Chronic**
	(1)	(2)	(3)
VaxRate	0.0016***	0.0711***	-0.0030***
	(0.0002)	(0.0035)	(0.0002)
xFemale	0.0001	-0.0023	0.0001
	(0.0001)	(0.0018)	(0.0001)
$\bar{y}$	0.6701	91.2055	0.3125

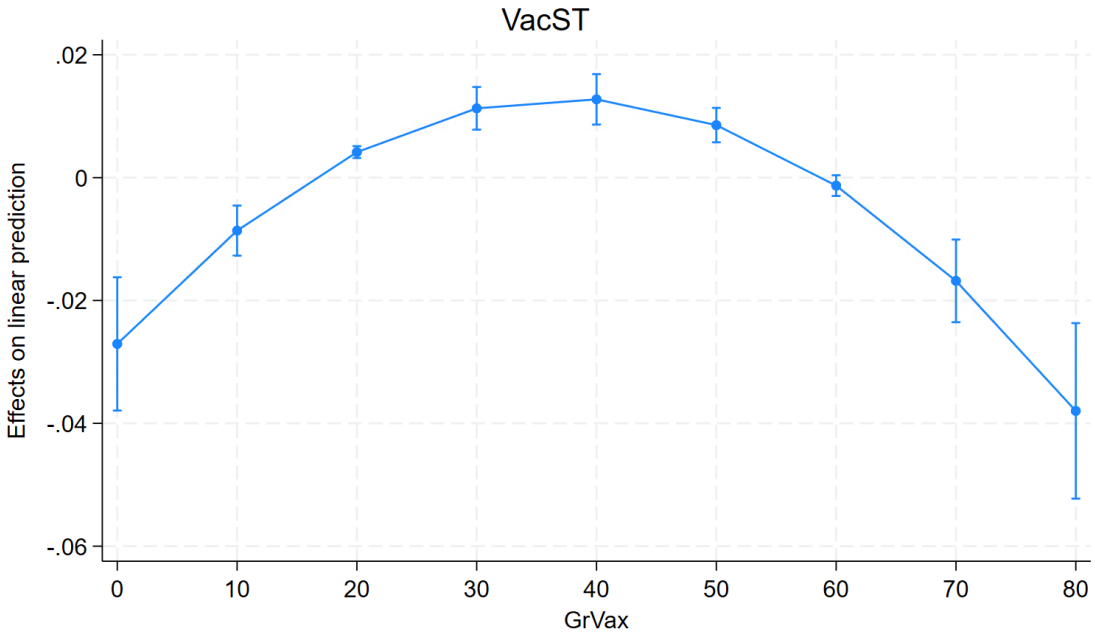
Note: Table reports 2SLS estimates allowing the effect of leave-one-out grademate vaccination to vary by gender. The main coefficient gives the estimated effect for male students; the interaction term gives the difference for female students. Peer vaccination, peer eligibility, and attendance are measured in percentage points. Own vaccination and chronic absenteeism are indicators. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table 6: IV Estimates of Peer Vaccination Effects: Schoolmates

	VaxST		AttRate		Chronic	
	(1)	(2)	(3)	(4)	(5)	(6)
SchVaxRate	0.0013***	0.0013***	0.0075	0.0059	-0.0003	-0.0003
	(0.0004)	(0.0004)	(0.0096)	(0.0098)	(0.0004)	(0.0004)
Age FE	Y	N	Y	N	Y	N
Grade FE	N	Y	N	Y	N	Y
$\bar{y}$	0.6701	0.6701	91.2055	91.2055	0.3125	0.3125

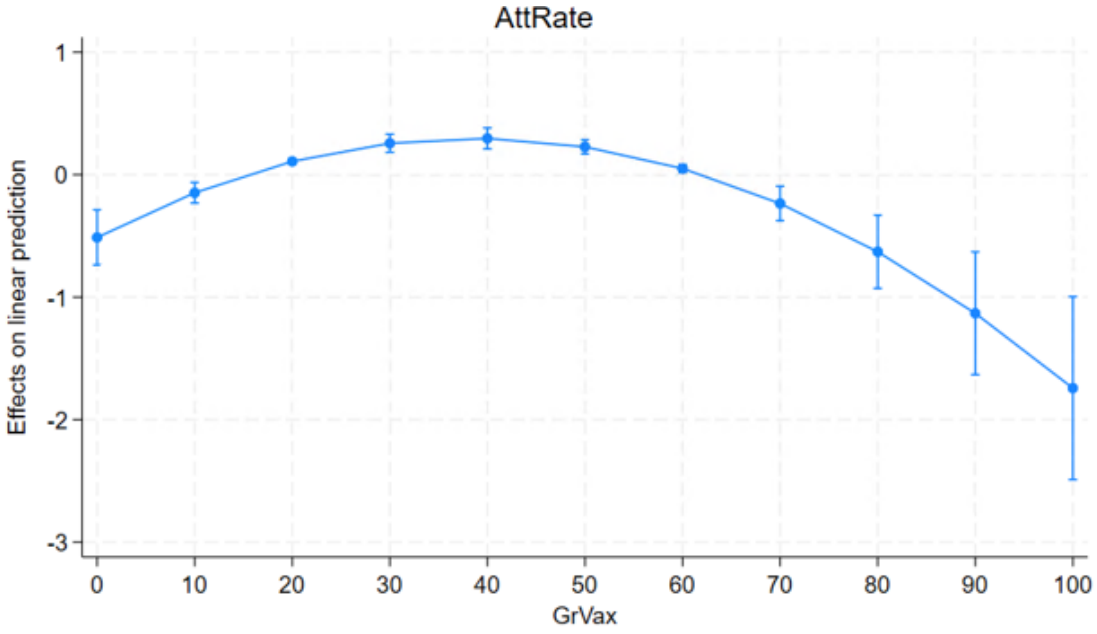
Note: Table reports 2SLS estimates using leave-one-out schoolmate vaccination as the peer measure, instrumented by leave-one-out schoolmate eligibility. Peer vaccination, peer eligibility, and attendance are measured in percentage points. Own vaccination and chronic absenteeism are indicators. All specifications include student controls. Columns 1, 3, and 5 include age-in-month fixed effects; columns 2, 4, and 6 include grade fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Standard errors clustered by school are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Figure 4: Marginal Effect of Grademate Vaccination on Own Take-up



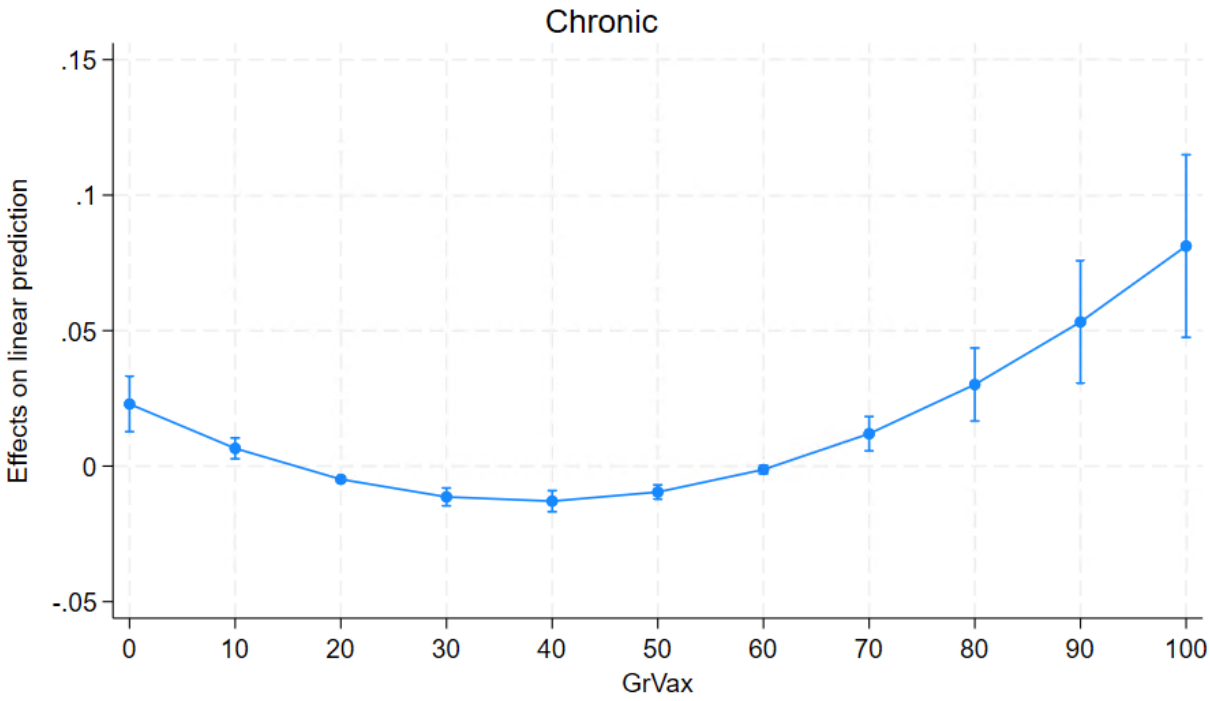
Note: Figure plots implied marginal effects from cubic 2SLS specifications of grademate vaccination. Grademate vaccination is instrumented using corresponding powers of grademate eligibility. Points show estimated marginal effects at different levels of grademate vaccination; bars show 95 percent confidence intervals.

Figure 5: Marginal Effect of Grademate Vaccination on Attendance Rate



Note: Figure plots implied marginal effects from cubic 2SLS specifications of grademate vaccination. Grademate vaccination is instrumented using corresponding powers of grademate eligibility. Points show estimated marginal effects at different levels of grademate vaccination; bars show 95 percent confidence intervals.

Figure 6: Marginal Effect of Grademate Vaccination on Chronic Absenteeism



Note: Figure plots implied marginal effects from cubic 2SLS specifications of grademate vaccination. Grademate vaccination is instrumented using corresponding powers of grademate eligibility. Points show estimated marginal effects at different levels of grademate vaccination; bars show 95 percent confidence intervals.

Appendix A.

Table A1: First-Stage Estimates for Race and Ethnicity Heterogeneity Models

	VaxRate				
		x Asian	x Black	x White	x Other
	(1)	(2)	(3)	(4)	(5)
EligRate	**0.551*****	-0.003	-0.000	-0.002	-0.000
	(0.007)	(0.002)	(0.001)	(0.002)	(0.000)
x Asian	0.102***	**0.668*****	-0.001	-0.001	0.000
	(0.009)	(0.010)	(0.001)	(0.002)	(0.000)
x Black	-0.094***	-0.000	**0.468*****	-0.000	-0.000
	(0.007)	(0.001)	(0.007)	(0.001)	(0.000)
x White	0.013	-0.001	-0.001	**0.579*****	0.000
	(0.012)	(0.003)	(0.001)	(0.012)	(0.000)
x Other	0.051***	0.002	-0.000	0.005	**0.603*****
	(0.008)	(0.003)	(0.002)	(0.003)	(0.010)
SW F	9,068	7,283	8,198	5,653	6,569
First Stage F	1,499	1,499	1,499	1,499	1,499
R^2	0.94	0.96	0.93	0.94	0.93

Note: The omitted race/ethnicity category is Hispanic. Peer vaccination and peer eligibility are measured in percentage points. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Sanderson-Windmeijer and Kleibergen-Paap first-stage F-statistics are reported. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A2: First-Stage Estimates for Gender Heterogeneity Models

	VaxRate	
		xFemale
	(1)	(2)
EligRate	0.5605***	-0.0036
	(0.0076)	(0.0050)
xFemale	-0.0332	0.5670***
	(0.0634)	(0.0090)
SW F	7,320	4,379
First Stage F	2,784	2,784
R^2	0.93	0.92

Note: Peer vaccination and peer eligibility are measured in percentage points. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Sanderson-Windmeijer and Kleibergen-Paap first-stage F-statistics are reported.

Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A3: First-Stage Estimates for Schoolmate Models

	SchVaxRate	
	(1)	(2)
SchEligRate	0.567***	0.567***
	(0.014)	(0.014)
Age FE	Y	N
Grade FE	N	Y
$\bar{y}$	31.704	31.704
R^2	0.62	0.62
N (Students)	170,837	170,837
First Stage F	1,750	1,741

Note: Table reports first-stage estimates for the schoolmate specifications. The dependent variable is leave-one-out schoolmate vaccination at school start, and the instrument is leave-one-out schoolmate eligibility at school start. Peer vaccination and peer eligibility are measured in percentage points. All specifications include student controls. Column 1 includes age-in-month fixed effects; column 2 includes grade fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Standard errors clustered by school are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A4: First-Stage Estimates for Nonlinear Models

	Cubic Model		
	VaxRate	$VaxRate^2$	$VaxRate^3$
	(3)	(4)	(5)
EligRate	2.0638***	186.0270***	15,532.0836***
	(0.1396)	(14.8473)	(1312.1467)
$EligRate^2$	-0.0339***	-3.8042***	-342.3029***
	(0.0028)	(0.3061)	(27.2725)
$EligRate^3$	0.0002***	0.0240***	2.1860***
	(0.0000)	(0.0017)	(0.1600)
First Stage F	12	12	12
R^2	0.94	0.86	0.78

Note: Table reports first-stage estimates for the nonlinear 2SLS specifications. In the quadratic model, grademate vaccination and its square are instrumented with grademate eligibility and its square. In the cubic model, grademate vaccination, its square, and its cube are instrumented with grademate eligibility, its square, and its cube. Peer vaccination and peer eligibility are measured in

percentage points. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Kleibergen-Paap first-stage F-statistics are reported. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A5: IV Estimates of Nonlinear Peer Vaccination Effects

	(1)	(2)	(3)
Panel A VaxST			
VaxRate	0.0017***	-0.0020***	-0.0271***
	(0.0001)	(0.0006)	(0.0055)
$VaxRate^2$		0.0001***	0.0011***
		(0.0000)	(0.0002)
$VaxRate^3$			-0.0000***
			(0.0000)
Panel B AttRate			
VaxRate	0.0700***	-0.0316*	-0.5126***
	(0.0034)	(0.0148)	(0.1147)
$VaxRate^2$		0.0018***	0.0209***
		(0.0003)	(0.0042)
$VaxRate^3$			-0.0002***
			(0.0000)
Panel C Chronic			
VaxRate	-0.0029***	-0.0010	0.0229***
	(0.0002)	(0.0006)	(0.0054)
$VaxRate^2$		-0.0001***	-0.0009***
		(0.0000)	(0.0002)
$VaxRate^3$			0.0000***
			(0.0000)

Note: Table reports 2SLS estimates from linear, quadratic, and cubic specifications of grademate vaccination. Grademate vaccination terms are instrumented using corresponding powers of grademate eligibility. Peer vaccination, peer eligibility, and attendance are measured in percentage points. Own vaccination and chronic absenteeism are indicators. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. Kleibergen-Paap first-stage F-statistics are reported. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A6: First-Stage Estimates for Alternative Vaccination Exposure Dates

	VaxRate	$VaxRate^{Oct}$	$VaxRate^{Feb}$	$VaxRate^{May}$
	(1)	(2)	(3)	(4)
EligRate	0.561***	0.6417***	0.1653***	0.1448***
	(0.008)	(0.0072)	(0.0038)	(0.0036)
First Stage F	5,561	7,946	1,932	1,664
R^2	0.93	0.95	0.91	0.91
N	170,837	170,837	170,837	170,837

Note: Table reports first-stage estimates using alternative dates to define grademate vaccination. The dependent variable is the leave-one-out grademate vaccination rate measured at school start, October 29, 2021, February 22, 2022, or May 23, 2022. The instrument is leave-one-out grademate eligibility measured at school start. Peer vaccination and peer eligibility are measured in percentage points. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. First-stage F-statistics are reported. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A7: IV Estimates of Peer Vaccination Effects by Alternative Exposure Date

	Sept 13th	Oct 29th	Feb 22nd	May 23rd
	(1)	(2)	(3)	(4)
		VaxST		
VaxRate	0.0017***	0.0015***	0.0057***	0.0065***
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
		AttRate		
VaxRate	0.0700***	0.0612***	0.2377***	0.2714***
	(0.0034)	(0.0029)	(0.0116)	(0.0119)
		Chronic		
VaxRate	-0.0029***	-0.0026***	-0.0100***	-0.0114***
	(0.0002)	(0.0001)	(0.0005)	(0.0006)

Note: Table reports 2SLS estimates using alternative dates to define grademate vaccination. In each column, leave-one-out grademate vaccination is measured on the date listed in the column heading and instrumented with leave-one-out grademate eligibility at school start. Peer vaccination, peer eligibility, and attendance are measured in percentage points. Own vaccination and chronic absenteeism are indicators. All specifications include student controls, school fixed effects, and age-in-month fixed effects. Student controls include indicators for race/ethnicity, female, SWD, EverELL, and Medicaid. First-stage F-statistics are reported. Standard errors clustered by school-grade are reported in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.