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Received: 22 March 2022 | Revised: 16 January 2023 | Accepted: 20 January 2023

DOI: 10.1002/hec.4657

RESEARCH ARTICLE

Health Economics WILEY

School-age vaccination, school openings and Covid-19 diffusion

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Abstract

This article investigates the relationship between school openings and Covid-19 diffusion when school-age vaccination becomes available. The analysis relies on a unique geo-referenced high frequency database on age of vaccination, Covid-19 cases and hospitalization indicators from the Italian region of Sicily. The study focuses on the change of Covid-19 diffusion after school opening in a homogeneous geographical territory (i.e., with the same control measures and surveillance systems, centrally coordinated by the Regional Government). The identification of causal effects derives from a comparison of the change in cases before and after school opening in the school year 2020/21, when vaccination was not available, and in 2021/22, when the vaccination campaign targeted individuals of age 12–19 and above 19. Results indicate that, while school opening determined an increase in the growth rate of Covid-19 cases in 2020/2021, this effect has been substantially reduced by school-age vaccination in 2021/2022. In particular, we find that an increase of approximately 10% in the vaccination rate of school-age population reduces the growth rate of Covid-19 cases after school opening by approximately 1%.

KEYWORDS

Covid-19 cases, Covid-19 vaccination, difference in differences, school openings

JEL CLASSIFICATION

I18, I28, C23

1 | INTRODUCTION

The Covid-19 pandemic determined the flourishing of a substantial amount of studies addressing the health and socio-economic determinants of its diffusion, aiming also at identifying measures tied to contain its direct and indirect costs for the society.

Schools, and the students' population, have been at the center of this discussion for at least two reasons. On the one hand, among the restrictive policies implemented during the first and second wave of the pandemic, when anti-Covid-19 vaccines were not available, school closure has been a widely adopted measure, together with more general measures of lockdown of economic activities. Closing the schools, and implementing distance learning, was based on the assumption that the interactions implied by attending schools might have been an important driver of the spread of Covid-19 in the population. The recent

We are grateful to the anonymous reviewers whose suggestions and detailed comments have substantially improved this manuscript. Usual caveat applies.

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literature addressing the issue, often exploiting school openings for identification purposes, found mixed results (see Svaleryd & Vlachos, 2022, for a detailed survey). On the other hand, closing the schools raised concerns on the costs in terms of lost opportunities of accumulating human capital, as well as on the psychological costs of the students and distress of students' families (see Stantcheva, 2022, and references therein).

In December 2020, following the approval by the Food and Drug Administration in the US and the European Medicines Agency, anti-Covid 19 vaccines became available and recommended for individuals older than 16 years, and were subsequently approved in May 2021 for adolescents in the age bracket 12–15. In this new context, some crucial questions naturally arise: when vaccination is available to the students' population, do school openings still represent a potential triggering factor of Covid-19 diffusion? Is school closure, therefore, still to be recommended as an effective mitigation policy?

In this article, we try to answer these questions by analyzing granular data from the Italian region of Sicily, comparing the effect of school openings during the school year 2020/21, when vaccines were not available, to the effect in 2021/22, when vaccines were available for the students' population and for the population at large. Considering granular data from a homogeneous territory (i.e., subjected to the same control measures and surveillance systems coordinated by the Regional Government), and the same period of the year may help to account for a wide range of social and institutional confounding factors and for the effects of seasonality. To the best of our knowledge, this is the first article studying whether school-age vaccination availability has the potential to fade out Covid-19 containment measures, such as school closures, by mitigating the effect of school openings on the spread of the infection.

Our analysis relies on a dataset obtained by merging geo-localized data on Covid-19 cases, information on age vaccination exposure, schools' geographical location and school opening dates. In particular, we build an indicator of local (i.e., at census micro-area level) vaccine exposure from detailed data on daily vaccinations by age at municipal level, and on the demographic structure of the census area population. Key to the identification strategy is the comparison of the effects of school openings on Covid-19 contagion spread before and after vaccination for the student population become available. In so doing, we are able to estimate whether school-age vaccination mitigates the impact of school opening on Covid-19 diffusion.

The empirical results suggest that school-age vaccination played a major role in reducing Covid-19 cases diffusion after school openings in Sicily. Specifically, we show that school opening in 2021/22 is associated with a differential impact when compared to 2020/21, with almost no effects on Covid-19 diffusion at the local level. The positive influence of school openings on Covid-19 diffusion, identified by Amodio et al. (2022), appears to be fully mitigated by vaccination. In addition, we document by a counterfactual analysis that the diffusion of vaccination is correlated with a reduction of hospitalizations in intensive care units (ICU) of approximately 19%.

The work is organized as follows. Section 2 provides a review of the relevant literature; Section 3 describes Covid-19 transmission and vaccinations in Sicily, while Section 4 introduces the dataset. Section 5 specifies the econometric models we utilize. Section 6 presents the main results, a set of robustness checks and a heterogeneity analysis; Section 7 concludes.

2 | SCHOOL OPENINGS, SCHOOL CLOSURES, VACCINATIONS AND COVID-19 DIFFUSION: A REVIEW OF THE LITERATURE

Our contribution speaks to three related strands of literature. The first one is about the effects of school openings on Covid-19 diffusion. The second refers to the efficacy of school closures as a mitigation policy. The third relates to the overall impact of vaccination in containing the epidemic.

The effects of school opening as a trigger of Covid-19 propagation are addressed by several studies. Among these, works such as Amodio et al. (2022), Chernozhukov et al. (2021), Vlachos et al. (2021) find a positive relationship between school openings and the growth rate of Covid-19 cases, in a range of 2%–5%. Differently, other studies point out non-significant or mixed results. In particular, Isphording et al. (2021a) analyze the German case taking into account the school openings after the summer break of 2020, and do not find a positive impact on Covid-19 diffusion. Yoon et al. (2020) focus on the first wave of Covid-19 in Korea and investigate the step-wize transition from school closure to opening, both online and offline, and conclude that offline schooling did not lead to any substantial outbreak among the youths. Additionally, Keeling et al. (2021) study eight different school reopening strategies implemented for primary and secondary schools in England. The authors observe a high degree of heterogeneity, with half-sized classes or younger cohorts not associated with increased levels of infections, and the reductions in community social distancing exacerbating the impacts of school openings. Finally, Ertem et al. (2021) identify regional differences of school openings in the US, with non-significant (positive and significant) effects in most of US (Southern) states, in a setting where diverse teaching methods (in-person, hybrid, remote) are controlled for. Our paper, however, is the first work comparing the impact of school openings on Covid-19 diffusion in a period with no vaccines

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available to a period in which vaccines were introduced and gradually extended to different age cohorts of the population, focusing on the effect of vaccination.[1]

An additional set of works investigates the effectiveness of school closures as a mitigating policy, especially during the first wave of Covid-19 pandemic. For example, Flaxman et al. (2020) find that lockdowns may substantially reduce Covid-19 transmission, but cannot identify a specific effect of school closures. This depends on the fact that they rely on a cross-country study which does not allow to disentangle the contribution of general lockdowns from the one of school closures. Differently, by implementing a panel data analysis of the effect of school closures in a sample of European countries, Alfano (2022) points out that, given a time lag of 10–40 days, school closures have a sizable, negative effect on Covid-19 diffusion, measured by daily cases of infections. Ferguson et al. (2020) study the case of mitigation policies in UK, and estimate the specific effect of school closures. They find that school closures have a sizable influence in reducing Covid-19 diffusion, estimated as a reduction of 14% of the peak demand of ICU beds. In contrast, Fukumoto et al. (2021) make use of municipality level data to investigate the effects of schools' closures in Japan during spring 2020 but identify no causal links of school closures in mitigating the spread of Covid-19. These studies, however, refer to a period in which vaccinations were not available and, therefore, any conclusion based on these results on the appropriateness of school closures as a mitigating policy should be re-evaluated at the time in which vaccines become available. None of these researches utilizes granular data as in this work, which allow to specifically focus on the school-age population while accounting for a number of confounding factors and, therefore, to formulate a more accurate evaluation of school closures as a mitigation policy. This is even more important given that, as mentioned in Section 1, school closures imply a host of negative effects, such as losses in human capital accumulation and earnings over the lifetime (see, e.g., Agostinelli et al., 2022; Psacharopoulos et al., 2021; Fuchs-Schundeln et al., 2020, and Stantcheva, 2022, for an updated account of the literature on this point).[2]

Finally, a growing literature started to analyze the impact of vaccinations on Covid-19 propagation. For example, the extensive study of Kim and Lee (2022) shows that vaccination reduced diffusion in the medium-run, together with other non-pharmaceutical interventions.

Among others, Heath et al. (2021) examine a set of more than 15,000 individuals who underwent randomization for Covid-19 vaccine, and find that the level of vaccination efficacy is about 86.3% against the Alpha variant, while raises up to 96.4% when considering the original variant. Francis et al. (2021) conduct a comprehensive review of Covid-19 vaccine sub-types evidencing the associated efficacy and their geographical distribution, uncovering that this varies between 66.9% for Janssen, widely diffused in North-America, South-America, South Africa and Europe, to 95% for Pfizer which covers the same continents but is widely distributed also in Australia and in the Middle-East. Other contributions explore the vaccination strategies to reach herd immunities and reduce contagion. For example, Cot et al. (2021) focus on human mobility and Covid-19 vaccines to investigate the effect of the US vaccination strategies on the pandemic dynamics in 2020/21. The authors point out that vaccination alone may not impede the outbreak of large contagions and that social distancing measures may become necessary until a high level of immunity is achieved. Coccia (2022) aims at identifying the optimal level of vaccination, expressed as number of doses per 100 inhabitants, for a sustained reduction in Covid-19 cases and deaths. The results of this study suggest that this level is reached when at least 80 doses of vaccines per 100 inhabitants are administered. Our article, however, is the first work that tries to assess the effectiveness of anti-Covid-19 vaccinations through a comparison of school openings when vaccines were not and were available. Besides providing estimates of the effect of school openings on Covid-19 diffusion in these two periods, we will propose an estimation by a counterfactual analysis, with some caveats described in Section 6.1, of the reduction in ICU hospitalizations due to school-age vaccinations. This may offer a more variegated policy answer based on cost-benefit analysis than opening or closing schools (and implementing other restrictions), insofar as there exists the additional element of health and non-health interventions.

3 | BACKGROUND: COVID-19 DIFFUSION AND VACCINATIONS IN SICILY

Sicily and the South of Italy have been only marginally affected by the Covid-19 pandemic during the first wave, but the level of Covid-19 cases substantially increased from the second wave onwards. This is clearly documented by the temporal trend of weekly new Covid-19 cases in Sicily in Figure 1,[3] where gray areas highlight the two school-opening windows under investigation in this work.[4] As shown in Figure 1, there was a dramatic increase in Covid-19 cases starting from late 2021, due to the predominance of the SARS-CoV-2 Omicron variant. This, however, occurred well after the time periods considered in this analysis and does not affect their comparability. Specifically, in the study period only two different variants were predominant: almost 100% Wild-type in September-October 2020 and around 90% Delta in September-October 2021 (Istituto Superiore di Sanità (ISS), 2021).

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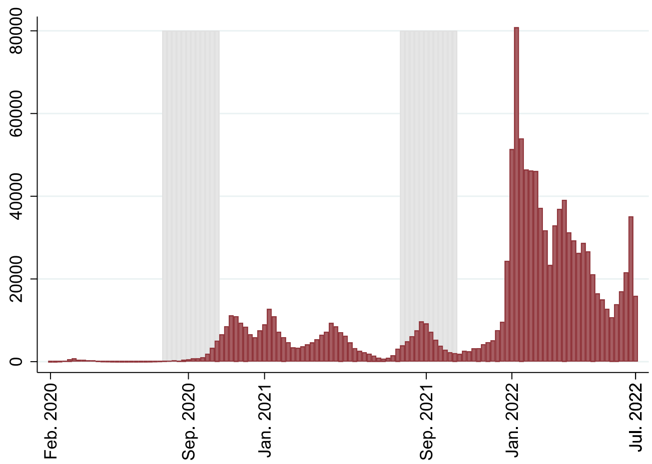

FIGURE 1 Weekly Covid-19 cases in Sicily, 2020–2022. [Colour figure can be viewed at wileyonlinelibrary.com]

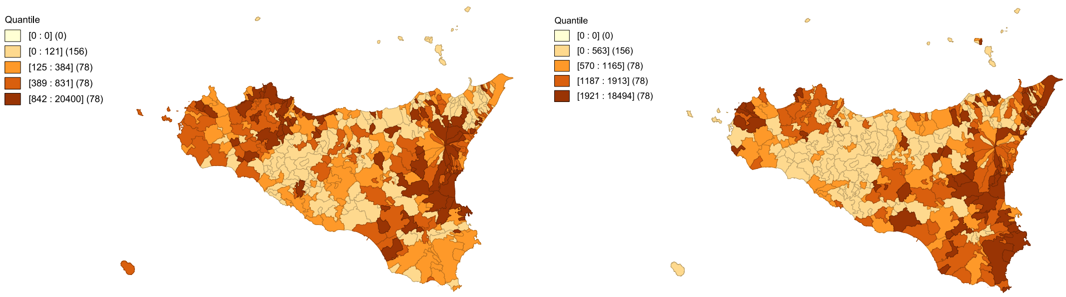

FIGURE 2 Covid-19 cases per one million population in 2020 (left) and 2021 (right). [Colour figure can be viewed at wileyonlinelibrary.com]

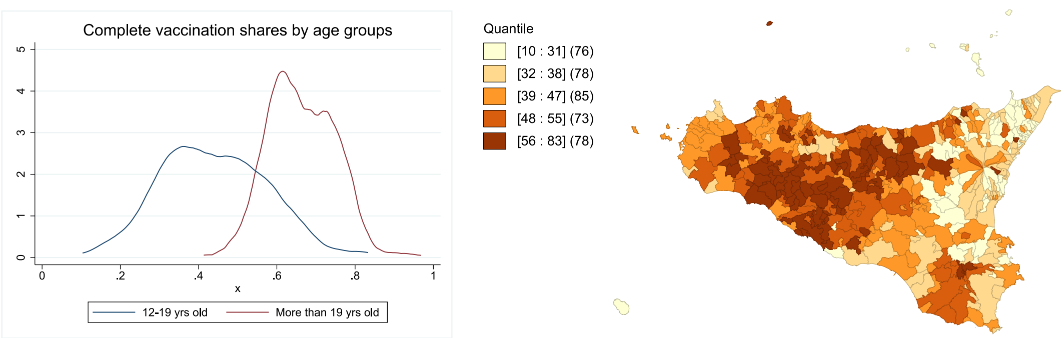

FIGURE 3 Vaccination rates: densities for different demographic groups (left panel), and distribution in the geographical space (right panel). [Colour figure can be viewed at wileyonlinelibrary.com]

Relatedly, Figure 2 displays the population-weighted Covid-19 cases (by quintiles) at the end of the summers of 2020 and 2021. While the number of cases is substantially higher in the second year (right panel), their spatial distribution follows similar paths, with higher infections in more touristic areas, such as the North-West and East coasts, and less cases in the inner areas, which are less populated and often mountainous.

As in the rest of Italy, the vaccination campaign started in January 2021 for the adult population, and was progressively extended to younger cohorts, up to June 2nd, 2021 when in Sicily (elsewhere in Italy this possibility was open by May 29th) every citizen older than 11 years was allowed to receive two doses of vaccine in a time window of 28 days. From June 30th, therefore, the population aged 12–19 had the possibility of being fully vaccinated, that is, of receiving two doses of anti-Covid-19 vaccine.

Figure 3 (left panel) shows the density of shares of vaccinated population across municipalities for two groups at the time of school opening in 2021: the school-age population, that is, of age 12–19,[5] and the population of age greater than 19. In particular, we see in Figure 3 (left panel) that in the school-age population the average is lower, which is expected because of the different timing of the vaccinations, but the variance is much higher than in the older group.

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Analogously, Figure 3 (right panel) indicates that vaccination rates for 12–19 years old display a wide heterogeneity across the geographical space, which adds up to the heterogeneity of Covid-19 cases in the geographical space highlighted in Figure 2.

Given these patterns of Covid-19 cases and vaccinations across space, we will consider the scenario in which Covid-19 contagion spreads locally and then has further spillovers. Specifically, we will follow the strategy of Amodio et al. (2022) and hypothesize that infections may be triggered by school openings in areas geographically close to the schools. In particular, we will assume that school openings affected the geographic micro-areas (i.e., the Italian census cells) within a ray of 1 km from the schools (in case of more than one school we will use a weighted average based on the number of students). In the next section, we provide the details on the dataset.

4 | DATA

The analysis relies on a set of data on 33,604 census cells observed four weeks before and four weeks after school openings in the school years 2020/21 and 2021/22. Census cells are micro-areas defined by the Italian National Statistical Office (ISTAT) to conduct the census of the population.[6] Sicily counts 36,681 census cells with an average population of about 152 inhabitants and a median area of 0.13 km^2. Part of these cells do not have any resident population and thus are excluded from the analysis. In our sample, therefore, the average cell population is equal to 152.33 inhabitants, of whom about 24 of school-age (5–19). When considering schools within 1 km distance from the cells, each cell is "exposed", on average, to 12.65 schools, while 29.2% of the cells are not neighboring any school. In total, our dataset comprises 4223 schools and 390 municipalities.

The dependent variable in our econometric analysis is the weekly change in the log of Covid-19 cases at census cell level obtained from Istituto Superiore di Sanità (ISS) (2020), which provides information on new Covid-19 cases on a daily basis.[7] We aggregate Covid-19 cases at weekly level to account for the serial time of infection (i.e., the median time to develop infection, after contagion), following the standard in the literature (see, e.g., Cereda et al., 2020).

To capture the effect of school openings, we build a dummy activating when at least one school attended by students in the age bracket 12–19 opens within a ray of 1 km from the centroid of a census area. This variable is equal to zero before the week in which school opened and takes on a value of one afterward, in both school years 2020/21 and 2021/22. We focus only on the 4223 public schools in Sicily, as these host more than 95% of students in the region, for grades where school is compulsory (in the periods considered, Sicily counts approximately 790,000 students, of which 240,000 in high schools).

From ISS (2020) we also gather data on vaccinations, which include information on the number of administered first and second doses by age. Differently from the Covid-19 cases, these data do not contain the indication of the census cell of residence of the vaccinated individual, so we can only utilize data on vaccinations at municipal level. We use these data to develop a set of indicators on vaccination coverage by age. First, for consistency, we create a variable on the total number of vaccinated individuals by class age and municipality. Then, we combine the vaccination data with population data from ISTAT to build two measures on the share of the 12–19 years old population and on the share of the population aged 19 or older, who received the first and second dose in a given municipality. Finally, we combine vaccination information at municipality level with age-structure information at cell level from the 2011 Census to develop a cell-level indicator measuring the exposure to vaccination in a census cell i as follows:

$$Exp\_Vaccines_{age,i} = \left(\frac{vaccines_{age,m}}{pop\_mun_{age,m}}\right) * \left(\frac{pop\_cens_{age,i}}{pop\_cens_i}\right), \tag{1}$$

where $age = \{12 - 19, >19\}$; $vaccines_{age,m}$ represents the number of vaccinated individuals (with either one or two doses) in age group age administered in Sicily at the date of September 16th, 2021 in municipality m, and $pop\_mun_{age,m}$ indicates the population in age group age in municipality m; $pop\_cens_{age,i}$ denotes the population in age group age in the census area i, while pop_cens_i represents the total population of census cell i.[8]

The logic of this variable is that the higher the share of vaccinated population in an age group within a municipality, and the higher the share of population of that age group in a census area, the more exposed the census area is to vaccination. The implicit assumption is that the within a city vaccination rates for an age group (i.e., 12–19 years old) are quite similar across census cells.[9]

Finally, we collected data on the total number of beds in ICU in the municipality's hospitals and, for the municipalities without ICU beds, on the distance of the municipality centroid from the closest hospital with an ICU. These data are gathered from the Italian Ministry of Health.[10] For a municipality hosting at least one hospital with ICU, the distance indicator takes the value of zero. For a municipality without a hospital with ICU, the number of beds takes a value equal to zero, while the distance takes a real positive value.

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TABLE 1 Summary statistics.

	Obs	Mean	Std. Dev.	Min	Max
Municipality level					
Share of vaccinated (12–19) (2 doses)	390	0.44	0.14	0.10	0.83
Share of vaccinated (12–19) (at least 1 dose)	390	1.07	0.27	0.25	1.72
Share of vaccinated (>19) (2 doses)	390	0.66	0.09	0.41	0.97
Share of vaccinated (>19) (at least 1 dose)	390	1.40	0.16	0.88	2.07
ICU beds	390	1.03	7.66	0	123
Census area level					
Covid-19 cases, growth rate (2020)	134,416	0.02	0.24	−3.26	3.95
Covid-19 cases, growth rate (2021)	100,812	−0.01	0.24	−3.14	2.40
Covid-19 cases, growth rate (2020–2021)	33,585	−0.03	0.11	−1.02	0.79
Exposure to vaccination (12–19) (2 doses)	32,490	0.04	0.03	0	0.31
Exposure to vaccination (12–19) (at least 1 dose)	32,490	0.09	0.06	0	0.73
Exposure to vaccination (>19) (2 doses)	32,490	0.52	0.12	0	0.93
Exposure to vaccination (>19) (at least 1 dose)	32,490	1.10	0.26	0	1.91

Table 1 reports the descriptive statistics of the variables, both at the municipality and census cell level, that we will use in the econometric analysis.[11]

In the next section, we describe our empirical strategy.

5 | EMPIRICAL STRATEGY

The empirical strategy relies on two main specifications. The first specification captures the differential effects between school opening in 2020/21 and 2021/22. We do this by using a Diff-in-Diff (DiD) dynamic process model with fixed effects and week dummies, as in Chernozhukov et al. (2021) and Amodio et al. (2022).[12]

The empirical specification takes the following form:

$$\Delta lnCovid_{i,t,y} = \alpha_i + \rho \Delta lnCovid_{i,t-1,y} + \sum_{j=3}^{4} \beta_j lnCovid_{i,t-j} + \lambda S_{i,t-2} + \eta S_{i,t-2} * Year_{2021/22} + \tau C_i + g T_t + u_{i,t} \tag{2}$$

with $i = 1, 2, \ldots, n$; $t = 1, 2, \ldots, T$; $y = 2020/21, 2021/22$;

where $\Delta lnCovid_{i,t,y}$ denotes the growth rate of Covid-19 cases in census area i in week t and school year y. The equation includes the lag of the dependent variable and the term $lnCovid_{i,t-j}$, denoting the natural logarithm of Covid-19 cases in the same census area i, measured at times $t-3$ and $t-4$, following an approach similar to Chernozhukov et al. (2021), who show that this can be seen as an empirical specification derived from a theoretical SIR model (see also Amodio et al., 2022). The main explanatory variable is the dummy $S_{i,t-2}$ on school openings, which takes value zero in the 4 weeks before the opening, and one after the week of school opening. As in Amodio et al. (2022), this variable enters with a 2-week lag to account for the time to detect the contagion, defined also as the serial time of infection. The coefficient λ captures the impact of school opening on Covid-19 diffusion and can be interpreted as a percentage increase in the growth rate. The term η denotes the coefficient of the interaction between the school opening dummy, $S_{i,t-2}$, and the year dummy $Year_{2021/22}$, and it aims at capturing the differential effect of school opening in the second year of the pandemic.[13] The model includes census area fixed effects C_i, to control for short term time-invariant unobserved characteristics, such as the population profile or level of education, and week dummies T_t, which account for common shocks in time, such as an increase in the number of Covid-19 tests available from a given week onwards.[14] Finally, the term $u_{i,t}$ is a robust error term clustered at census area level.[15]

In a second specification, we study whether the differential increase in Covid-19 cases during the four weeks following school opening in 2021/22 and in 2020/21 can be attributed to school-age vaccinated population, and how this effect compares to the one associated with the vaccinated population of age higher than 19.[16]

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To do so, we average our dependent variable across the 4 weeks after school opening in every census cell i, and take the first-difference of this new variable across the two school years. This is done to avoid zero-inflated regressions given the high level of granularity of our dataset, and the fact that the post-summer period brings to few cases in many census areas. Defining k as the week of school opening we have, therefore, $Y_i = \frac{\sum_{k=1}^{4} \Delta lnCovid_{i,k,2021/22}}{4} - \frac{\sum_{k=1}^{4} \Delta lnCovid_{i,k,2020/21}}{4}$.

The new model, having Y_i as dependent variable, takes the following form:

$$Y_i = \alpha_i + \nu_1 \Delta Exp\_Vaccines_{age=12-19,i} + \nu_2 \Delta Exp\_Vaccines_{age>19,i} + \theta Y_{i,k-4} + \zeta Mun_c + \omega_i, \tag{3}$$

where $Exp\_Vaccines_{age=12-19,i}$ and $Exp\_Vaccines_{age>19,i}$ are two indicators of the exposure to vaccination for individuals of age between 12 and 19 and above 19 at census area level belonging to municipality c, built following the procedure introduced in Section 4. Given that vaccination was implemented only from December 27th, 2020, these shares are equal to zero for the school year 2020/21, making $\Delta Exp\_Vaccines_{age=12-19,i} = Exp\_Vaccines_{age=12-19,i}$ and $\Delta Exp\_Vaccines_{age>19,i} = Exp\_Vaccines_{age>19,i}$, respectively. The term $Y_{i,k-4}$ denotes the lag of the dependent variable measured the 4 weeks before the school opening. Additionally, the control variables include a set of municipality-level dummies (Mun_c) to capture residual local unobserved characteristics (we exclude them in the initial specification because the municipality dummies are dropped by differencing). Equation (3) can be considered as a first-difference version of Equation (2) where the dependent variable is averaged across 4 weeks, to avoid zero inflated regression, and where the census area fixed effects and the week dummies are canceled out. In this framework, we still account for the initial conditions of the Covid-19 process at school openings, to control for possible differences in the phase of the epidemic between 2021/22 and 2020/21. Finally, ω_i is the error term clustered at the census area level.

6 | ECONOMETRIC ANALYSIS

In this section, we present the results of the estimation of Equations (2) and (3). In particular, Section 6.1 illustrates our benchmark findings, while Section 6.2 contains the results on the identification of heterogeneous effects and of robustness tests. Section 6.1 also contains the outcomes of a counterfactual analysis in which we estimate the impact of vaccinations on the number of Covid-19 cases and on ICU beds occupancy by Covid-19 patients.

6.1 | Benchmark results

Table 2 reports the results of the estimation of Equation (2). Specifically, Columns (1) and (2) show the coefficients from Equation (2) when the two school years are kept separated. These indicate that the two coefficients of school opening diverge substantially in magnitude and significance level in the two school years. In particular, the coefficient measuring the impact of school opening in 2020/21 on Covid-19 diffusion, λ, is positive, significant and in line with the literature also in terms of magnitude. Compared to Amodio et al. (2022), the coefficient is slightly lower as the time windows under consideration here are shorter.[17]

The estimated coefficient for school opening in 2021/22 is not significantly different from zero, indicating that school opening is not associated with an increase in the growth rate of Covid-19 cases.[18] This finding suggests that school opening after vaccination was made available did not affect the diffusion of Covid-19, pointing to the fact that a restriction, such as school closure, may be not justified under these conditions. Such an outcome is confirmed when we estimate the specification on the full sample. Results in Column (3) of Table 2 reveal that the coefficient for school opening remains positive and significant, while the coefficient of the interaction between school opening and the year dummy for 2021, η, is negative, generating a null overall effect. Once again, this provides an indication that school opening in 2021 had no significant impacts on Covid-19 diffusion, as also confirmed by the t-test on the equality of the absolute value of the two coefficients reported at the bottom of Column (3).

Finally, we slightly modify the baseline specification by adding an indicator on the log number of vaccinated individuals (with second dose) of school-age calculated at the time of school opening and at municipality level. Since this indicator is not time-varying, we just create a new interaction term by multiplying it with the school opening in 2021 variable. The coefficient reported in Column (4) of Table 2 suggests a strongly significant negative effect of this new interaction term, with less school opening induced cases in areas where the number of vaccinated individuals was higher. In terms of magnitude, an increase of, for example, 15% in the vaccinated individuals aged 12–19, corresponding to the difference between Partinico and Paternò (two small towns near Palermo and Catania), appears to fully compensate the effect of school opening on Covid-19 diffusion.[19] Overall, these results suggest that vaccination of individuals aged between 12 and 19 may have significantly contributed to the absence of any impact of school opening on Covid-19 diffusion at the beginning of the 2021/22 school year.

TABLE 2 Covid-19 cases, school opening and vaccines.

	Dep. Var.: Change ln of Covid-19			
	(1)	(2)	(3)	(4)
Specification	**Year = 2020/21**	**Year = 2021/22**	**Full sample**	**Full sample**
School opening (λ)	0.013***	0.001	0.015***	0.015***
	(0.002)	(0.002)	(0.001)	(0.002)
School opening X Year = 2021 (η)			−0.016***	−0.005
			(0.002)	(0.005)
School opening X Year = 2021/22 X ln of vaccinated (12–19)				−0.001**
				(0.001)
Δ ln Covid (lag, ρ)	−0.561***	−0.436***	−0.454***	−0.454***
	(0.005)	(0.003)	(0.002)	(0.002)
ln Covid (t−3, β_3)	−0.038***	−0.077***	−0.099***	−0.099***
	(0.011)	(0.004)	(0.003)	(0.003)
ln Covid (t−4, β_4)	−0.008	−0.011***	−0.039***	−0.039***
	(0.011)	(0.004)	(0.003)	(0.003)
Test on school opening (prob. > 0)				
$\lambda_{2020/21} + \lambda_{2021/22} = 0$	-	-	0.23	-
Census area fixed effects	Y	Y	Y	Y
Week dummies	Y	Y	Y	Y
Year of lag var.	2020	2021	2020 & 2021	2020 & 2021
Observations	268,832	268,832	537,664	537,664
Number of census areas	33,604	33,604	33,604	33,604
R^2 within	0.22	0.22	0.21	0.21

Note: The table displays the results from Fixed-Effects estimates at census area level with weekly dummies. The dependent variable is the change in log of the weekly Covid-19 cases. The year 2021 dummy is added only in the interaction as it would be collinear with the week dummies. The indicator ln of Vaccinated (12–19) denotes the natural logarithm of the number of fully vaccinated individuals in school-age (12–19 years old) at the time of school opening at municipality level. This indicator is time invariant and it enters in the specification only in the interaction. Standard errors are clustered at census area level. The full version is reported in Table A4 of the Appendix.

***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 3 reports the coefficients obtained from the estimation of Equation (3) in which the effect of school-age vaccination is correlated to the average growth rate of Covid-19 cases in a window of four weeks after the school opening, in 2020 and 2021. Column (1) shows that school-age vaccination, measured at cell level through the exposure variable (second dose), captured by ν_1, is associated with a strongly significant negative effect. This turns out to be robust to the inclusion of: i) the initial conditions, that is, the change in the growth rate of Covid-19 cases in the 4 weeks preceding the school opening (Column 2); ii) municipality fixed effects (Column 3); iii) vaccination exposure in the population older than 19 years, captured by ν_2 (Column 4). Indeed, the coefficient related to vaccination of school-age population increases in magnitude with these controls. Specifically, the coefficient of the exposure variable, reported in Column (4), suggests that a 1% increase on the average level of exposure to vaccination of individuals aged 12–19 leads to a decrease of about 0.14% in the growth rate of Covid-19 cases.[20]

As an implication of the results in Table 3, in what follows we propose an estimation of the reduction in Covid-19 cases and hospitalizations in ICU for Covid-19 patients,[21] implied by school-age vaccination. Specifically, we compute the cumulated value of the new infections we would have observed if school-age vaccination had not been administered. This means predicting the new number of cases using the specification in Column (4) of Table 3, but imposing school-age vaccination equal to zero.

We first build the counterfactual difference between Covid-19 cases' growth rates in 2020 and 2021 with school-age shares of school-age vaccinated individuals equal to zero. Then we replace this difference to the Covid-19 growth rate of infections in 2020 to build the counterfactual growth rate of 2021. Ultimately, starting from the level of Covid-19 cases in 2021 before school openings, we derive the cumulated Covid-19 cases of the four weeks of 2021 after school opening. Such an exercise highlights that, without school-age vaccination, the new weekly infections would have increased, on average, by 11% (407 vs. 362) at municipality level.

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TABLE 3 Covid-19 cases in different schooling years and the role of vaccines.

	Dep. Var.: Y_i = change in the growth rate of Covid-19 cases post school opening (2021-2020)			
	(1)	(2)	(3)	(4)
Exposure to vaccines (age = 12–19), (ν_1)	−0.079***	−0.087***	−0.132***	−0.141***
	(0.015)	(0.015)	(0.015)	(0.015)
Exposure to vaccines (age > 19), (ν_2)				−0.011***
				(0.004)
Change in the growth rate of Covid-19 cases pre-school opening (θ)		−0.062***	−0.055***	−0.055***
		(0.011)	(0.010)	(0.010)
Observations	32,490	32,490	32,490	32,490
R^2	0.001	0.004	0.085	0.085
Municipality dummies	N	N	Y	Y

Note: Standard errors are clustered at census area level.

***, **, and * denote significance at 1%, 5%, and 10%, respectively.

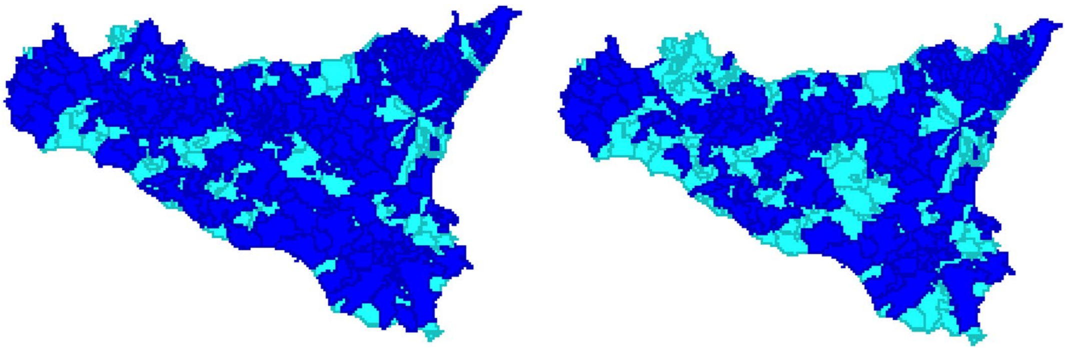

FIGURE 4 Municipalities with more than 20.7 Covid-19 cases per 1000 inhabitants (dark blue): counterfactual (left panel) and actual (right panel) scenarios. [Colour figure can be viewed at wileyonlinelibrary.com]

In this regard, Figure 4 reports the comparison of the municipality average cases in the counterfactual (left panel) and actual (right panel) scenarios. Dark blue represents municipalities with more than the median value (20.7) of new Covid-19 infections per 1000 inhabitants. On average, the number of cases per 1000 inhabitants increases from 26.98 to 29.07. This seems to be a realistic result, given that the share of population aged 12–19 in Sicily is 8.3% of the total population, even if it is likely to have higher interactions compared to older cohorts.

On the basis of this counterfactual results, we can conduct an exploratory exercise with the scope of predicting some potential effects of the anti-Covid-19 vaccination. In particular, the rule for imposing restrictions on economic and social activities in Italy assumes, among other parameters, a municipality average occupancy by Covid-19 patients, respectively, of 10% and 30% of ICU beds.[22]

The average municipality number of ICU beds in Sicily is 1.02, but this value is driven by small municipalities without ICU beds.[23] Conditional on having at least an ICU bed, the average number would be 13.86, with an Interquartile Range (IQR) of 4. Consequently, in a very conservative scenario for this smaller set of municipalities with ICU beds, this implies reaching the critical ICU parameter for the declaration of "yellow zone" and "red zone" status, respectively, with the second and fifth ICU bed occupied by a Covid-19 patient.

We can make an attempt of translating the counterfactual scenario in terms of ICU beds occupancy. Given that the ratio between active Covid-19 cases and ICU patients was 236.5 in Sicily during the four weeks after the 2021/22 school openings of September 16th, the resulting cases from our counterfactual scenario - with no school-age vaccinations - would have implied a 19.03% rise of ICU beds occupancy by Covid-19 patients.[24] Albeit suggestive, this exercise should be taken with caution as it is tied to a set of assumptions, such as keeping constant both the number of ICU beds and the ratio between active Covid-19 cases and ICU patients.

In addition, in this simulation we could not take into account a crucial factor, namely the age-structure of the infected population, which may influence bed occupancy in ICUs, as the infection affects more severely the older population. Since

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the age-structure of bed occupancy in ICUs is not available, we could not implement a more refined simulation relating the age-structure of the infected population to the age-structure in ICUs. However, given that data on the age-structure of the whole population are available, we carried out a simple accounting exercise suggesting that our results might be quite conservative. In fact, if we exclude "older" municipalities from the sample (i.e., municipalities with a share of population older than 60 years higher than the average share across Sicilian municipalities), which account for approximately 20% of the Sicilian population, the counterfactual occupancy of ICU beds by Covid-19 patients rises to 33%, instead of the estimated 19.03% mentioned above.[25]

6.2 | Heterogeneity and robustness

We carried out a set of exercises to test whether the relationship between Covid-19 cases, vaccination and school opening may be heterogeneous across a set of socio-demographic characteristics that may be linked to Covid-19 diffusion. Specifically, we test for heterogeneity across population density, classroom size and vaccination share of the whole population, by estimating Equation (3) on two subsamples deriving from splitting the sample by the median value of these dimensions.[26] Figure 5 presents the whisker plot of the coefficients obtained from this exercise, reporting in the top row the benchmark case (i.e., the one based on Column (4) of Table 3) for comparison purposes, while Table A1 in the Appendix reports the full sets of coefficients.

As Figure 5 shows, the coefficients of the exposure variables are all significant and negative, and the confidence intervals for most of them largely overlap. Interestingly, the only dimension for which the two coefficients do not largely overlap is the density of population, suggesting that the association between the vaccination exposure and new cases is larger, in absolute terms, for areas with lower population density.

This findings is in line with the analysis of the Sicilian case by Amodio et al. (2022) who observe that the role played by school openings is higher in less density populated areas. We can conjecture that the effect we identified here may depend on the fact that, in less densely populated areas, the share of social interactions implied by school openings is higher than in more populated areas, as suggested by Sato and Zenou (2015), who point out that in low-population density areas most of the social interactions is based on strong ties, such as family relationships, which are a relevant case of the interactions implied by school attendance. Differently, in high-population density areas the higher level of social interactions is based on "weak ties", that is, on less structured connections. If this is the case, therefore, the mitigation effect of the school-age vaccination is higher in more sparsely populated areas. Nevertheless, given that other aspects correlated to population density can be relevant (i.e., adherence to public health guidance), we consider this effect as a robust correlation, suggesting an interesting topic for further research.

Ultimately, we verified the robustness of our main outcomes through a set of additional exercises, that we compare to those of our preferred specification (i.e., Column (3) of Table 2), which are also reported in Column (1) of Table A2 in the Appendix, containing the results of the robustness tests. First, we tested for eventual bias stemming from the inclusion of the lagged dependent variable in the dynamic process of Equation (2). This is done following the work of Chernozhukov et al. (2021),

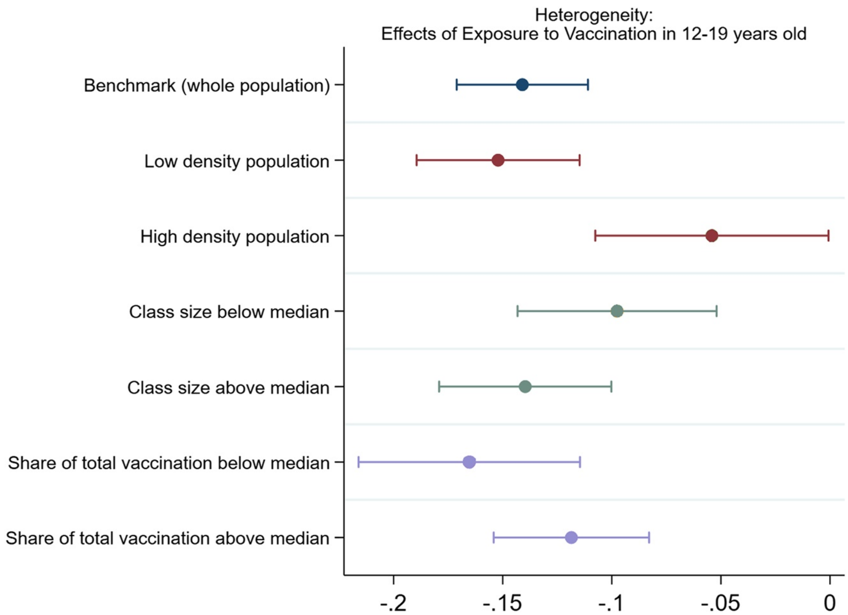

FIGURE 5 Heterogeneous effects of exposure to vaccination in 12–19 years old. [Colour figure can be viewed at wileyonlinelibrary.com]

which uses the Analytical Bias Correction estimator of Chen et al. (2019) to take into account the potential Nickell bias in this process. Column (2) of Table A2 shows that our outcomes are substantially unchanged. Subsequently, we checked whether the definition of the time window may affect the results. We therefore extended the time window up to 8 weeks before and after the school opening and run the baseline specification, without finding any appreciable difference (Column (3) of Table A2). We then took into account potential spillover effects due by the school opening, by using the process of Conley (1999), implemented by Colella et al. (2020). Column (4) of Table A2 reveals that the coefficients remain consistent. Finally, we modeled school opening in 2020/21 through propensity scores, to take into account the small flexibility implied by the *referendum*, following the same procedure of Amodio et al. (2022). Column (5) of Table A2 indicates that the results remain robust when accounting for this potential source of endogeneity (see Amodio et al., 2022, for more details on the use of propensity scores).

We also carried out a set of robustness tests on the specification of Equation (3), where we changed the definition of the dependent variable and used the share of population that received a single dose of vaccine only. As reported in Table A3 of the Appendix, in which Column (1) contains our benchmark findings, that is, those in Column (4) of Table 3, the coefficients appear slightly more variable in Columns (2) and (4), but this is likely to depend on the change in the scale of the dependent and independent variables, which are hereby computed differently from before. In particular, in Column (2) of Table A3 we consider an alternative specification in which we rearrange the time span of the regression as follows: (i) the dependent variable is computed as the growth rate of Covid-19 cases in the 4 weeks after school reopening in 2020/21 and 2021/22, and (ii) the control variable is given by the level of Covid-19 infections in the 4 weeks before school opening in 2020/21. Differently, in Column (4) of Table A3 we consider the first vaccination dose to build the exposure variable, whose average is 2.3 times bigger than in the benchmark case, so that if we apply this change to the coefficient (i.e., −0.059) we obtain −0.13, which is in line with the benchmark value. As we can observe, even with different definitions of the relevant variables, the results are strongly consistent. Finally, Column (5) of Table A3 contains the outcomes obtained when standard errors are clustered at municipality level, showing no appreciable modifications of the main results we obtain.

7 | CONCLUSIONS

The Covid-19 pandemic hit all countries as an unexpected shock in 2020 when few pharmaceutical tools were present. This implied that the first set of governmental reactions was mainly based on restrictions on individuals' mobility to lower the frequency of interactions and the consequent spread of the virus. Subsequently, medical treatments, mostly in the forms of vaccines, allowed to increase and improve the set of tools to contrast the Covid-19 diffusion, which started to imply a trade-off in using the restrictions. The evidence presented in this paper shows that school-age vaccination had a substantial role in reducing, basically neutralizing, the effect of school openings on Covid-19 diffusion. With a focus on Sicily and on a rich set of granular data, while school openings were a substantial driver of cases in 2020, this effect disappears in 2021, when school-age vaccination became available.

Our results reveal that an additional 1% of vaccination in the age cohort 12–19 (attending middle and high school) is associated with a decrease of 0.14% in the Covid-19 growth rate of cases in the post-summer school reopening period at local level. Also, in an exploratory counterfactual analysis that, however, cannot fully take into account age-related differences in infections and ICU bed occupancy, we document that school-age vaccination is correlated with an estimated reduction of 19% occupancy of ICU beds by Covid-19 patients, which implies a sizable effect on the possibility of municipalities to escape the restrictions which would be otherwise implemented by the State. The policy implications arising from this result are substantial, as it suggests that the campaign of school-age vaccination has potentially faded out or reduced the necessity of certain mitigation measures, such as school closures, to contrast the diffusion of Covid-19 pandemic. However, it is also important to stress that this finding derives from a study framed before the Omicron variant of Covid-19 became predominant, and thus more general policy conclusions need to be left for future research.

Additional points are left to future agenda, which may reveal whether our outcomes represent a lower or an upper bound. Specifically, in this paper we assumed that attitudes of vaccinated individuals do not change,[27] while individual restrictions affecting unvaccinated citizens in Italy (even if only for people older than 17, a small share of our class age) may imply a higher mobility by vaccinated individuals, so that the mitigation effect caused by vaccination should be counterfactually lower. Then, we could take into account that the school opening takes place in a post-summer period so that, due to the seasonality, we would observe less cases. This means that our findings could be a lower bound, because in a period of larger spread of diffusion and lower reliability of tracing (as, for instance, during Omicron waves, occurred after our observed time window) this impact could have been larger.

Ultimately, the present study may be limited by the fact that the two periods under investigation included two different SARS-CoV-2 variants, (Wild-type and Delta, respectively) and, possibly, some differences in behavior and policy factors could

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have occurred. However, although a precise evaluation of the contribution of these changes is difficult to gauge (even though we took it at least partially into account in the empirical analysis, see footnote 5), we have to consider that the Delta variant was documented to have a greater transmissibility with respect to Wild-type (see, e.g., Callaway, 2021) whereas behavior and policy factors in 2021 were relatively less stringent (see, for instance, the Covid-19 government response tracker developed by Hale et al., 2021).

According to the previous considerations, since in 2021 the probability of the viral diffusion could be considered higher than in 2020, it can be not excluded that our results can underestimate the contribution of vaccination in reducing the spread of SARS-CoV-2 correlated to school openings.

ACKNOWLEDGMENTS

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Open Access Funding provided by Universita degli Studi di Palermo within the CRUI-CARE Agreement.

CONFLICT OF INTEREST STATEMENT

The authors claim that they have no conflict of interest to report.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

1 A partial exception is Isphording et al. (2021b), who also analyze a period in which vaccination was available in Germany. However, they do not focus on the role of vaccinations, but on the effect of mandatory testing in schools, concluding that this can be an effective policy to contain the infection when schools are open.

2 Other studies considered different mitigation policies related to schools, such as social distancing. See, for example, van den Berg et al. (2021).

3 Data were collected from the Italian Civil Protection Department on July 4th, 2022, at: https://github.com/pcm-dpc/COVID-19/tree/master/dati-regioni.

4 The two school opening dates are September 24th, 2020 for the school year 2020/21 and September 16th, 2021 for the school year 2021/22.

5 By considering the age bracket 12–19, we are analyzing students attending compulsory school (*scuola media*), up to age 13, and students attending high-school. The lower bound of this age bracket is given to the lowest age for which vaccination was available at the time of school openings in 2021, while the upper bound is given by the age at which students attend the last year of high-school. Vaccinations for pupils younger than 12, that is, in the age bracket 5–11, were introduced in Italy only in December 2021.

6 The last census in Italy was conducted in 2011. This represents the most recent census for which data are available.

7 To include the zero-valued observations we add 1 before taking the log. This result is robust when using the Inverse Hyperbolic Transformation developed by Bellemare and Wichman (2020).

8 We exclude unreliable values for the share of 12–19 individuals (i.e., greater than 50%), probably due to measurement errors, at the census area level. These account for less than 0.1% of total observations. Results of the empirical analysis are consistent with the inclusion of these observations, and are available upon request.

9 Lacking census level vaccination data we may quote anecdotal evidence supporting this assumption, especially in the age range 12–19 where the expected differences in terms of, for example, education and habits, appear to be rather low. For instance, Tiu et al. (2021) show that the difference in vaccination at county level seems to matter even if all the under-vaccination clusters have strong state characteristics. On the other hand, only 3 municipalities out of 390 in our sample have more than 200,000 inhabitants, so that the room for high within-city heterogeneity seems rather limited. If we exclude these 3 municipalities, or all those with more than 100,000 inhabitants (losing, respectively, 15% and 18% of observations) results are consistent with those presented below.

10 Data on health structures are available at: https://www.salute.gov.it/portale/documentazione/p6_2_8_1.jsp.

11 In Table 1, by "share" we refer to the number of vaccine doses divided by the population. For example, an individual that received two doses is counted twice in the calculation of the share. For this reason, the share referred to receiving at least one dose can be greater than one.

12 With respect to Amodio et al. (2022), the time windows under consideration are shorter. This is done to avoid further confounding factors, such as the beginning of the colder season and the spread of the Omicron variant, which was observed from November 2021 in Italy (see Figure 1).

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[13] We do not include the $Year_{2021/22}$ dummy alone as this is collinear to the week dummies T_t.

[14] The week and census area dummies should also control for differences in the two periods under investigation in both the characteristics of Covid-19 variants (transmissibility, severity of the disease, susceptibility to treatments, etc.), and of other relevant factors, such as differences in individuals' behavior and policies. As we explain in Section 7, however, our results should not in any case be affected by such differences.

[15] In the robustness checks we will also consider standard errors clustered at municipal level to take into account treatment assignment.

[16] We refer to vaccinated population/individuals as the one(s) who received two doses of Covid-19 vaccine. To test this assumption, we consider individuals receiving at least one dose in some specifications reported in the robustness tests.

[17] The evaluation of other time windows is discussed in Section 6.2.

[18] While in principle school opening may be considered as endogenous, in practice in 2020/21 it corresponded to a staggered design due to a national *referendum* for which some schools were used as polling stations (see Amodio et al., 2022 for details), while in 2021/22 a unique equal opening date was fixed for all schools, irrespectively of the number of Covid-19 cases or ICU occupancy.

[19] The magnitude of the effect can also be appreciated by a comparison with the coefficients for the week dummies reported in Table A4 of the Appendix. In particular, it can be observed that in Column (2) of Table A4 the coefficients for the weekly dummies for the school year 2021/2022 are negative, highly significant and of relatively large magnitude. However, when the effect of vaccinations of school-age population is introduced in Columns (3) and (4), respectively by an interaction term and by the explicit consideration of the vaccinated population, the magnitude of the weekly dummies is strongly reduced.

[20] It is necessary to specify that, on average, the 12–19 population represents approximately 10% of the cell population, therefore the exposure variable is bounded upwards.

[21] This information is gathered by the Italian National Institute of Health and are made available by the Italian Civil Protection at the following link: https://github.com/pcm-dpc/COVID-19/tree/master/dati-regioni.

[22] These two levels correspond to the main policy instruments introduced in Italy, consisting in establishing the so-called "yellow" and "red zones", respectively implying some minor restrictions, such as wearing face masks in open areas, and major restrictions, including school closures and limitations on mobility.

[23] The average distance of a municipality without ICU beds from the nearest municipality with ICU beds is 3.1 km.

[24] Such increment in occupancy rate ranges between 12.5% and 25.9% when considering the below and above 95% confidence intervals of the means in the actual and counterfactual scenarios.

[25] We believe that this might depend on the fact that the age-structure can actually play two contrasting roles in the case we are studying. On the one hand, *i*) a higher ratio of older population might imply a larger number of beds occupancy in ICUs; on the other hand, ii) a higher share of older population might imply lower Covid-19 diffusion with respect to the school openings (at least in the short run), as older people might be less involved in the social interactions implied by the school openings. Our simple exercise allows to speculate that a factor like ii) might prevail, but clearly this represents a topic for further research.

[26] We obtained similar results when splitting the sample above and below the mean values. Results are available upon request.

[27] If the evidence of Andersson et al. (2021) holds, we should expect vaccinated individuals to implement lower social distances than non-vaccinated individuals so that, ceteris paribus, the effects of vaccination could have been bigger.

REFERENCES

Agostinelli, F., Doepke, M., Sorrenti, G., & Zilibotti, F. (2022). When the great equalizer shuts down: Schools, peers, and parents in pandemic times. *Journal of Public Economics*, *206*, 104574. https://doi.org/10.1016/j.jpubeco.2021.104574

Alfano, V. (2022). The effects of school closures on covid-19: A cross-country panel analysis. *Applied Health Economics and Health Policy*, *20*(2), 223–233. https://doi.org/10.1007/s40258-021-00702-z

Amodio, E., Battisti, M., Kourtellos, A., Maggio, G., & Maida, C. M. (2022). Schools opening and covid-19 diffusion: Evidence from geolocalized microdata. *European Economic Review*, 104003.

Andersson, O., Campos-Mercade, P., Meier, A. N., & Wengström, E. (2021). Anticipation of covid-19 vaccines reduces willingness to socially distance. *Journal of Health Economics*, *80*, 102530. https://doi.org/10.1016/j.jhealeco.2021.102530

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics & Statistics*, *82*(1), 50–61. https://doi.org/10.1111/obes.12325

Callaway, E. (2021). Delta coronavirus variant: Scientists brace for impact. *Nature*, *595*(7865), 17–18. https://doi.org/10.1038/d41586-021-01696-3

Cereda, D., Tirani, M., Rovida, F., Demicheli, V., Ajelli, M., Poletti, P., Trentini, F., Guzzetta, G., Marziano, V., Barone, A., Magoni, M., Deandrea, S., Diurno, G., Lombardo, M., Faccini, M., Pan, A., Bruno, R., Pariani, E., Grasselli, G., & Merler, S. (2020). The early phase of the covid-19 outbreak in Lombardy, Italy. *arXiv preprint arXiv:2003.09320*.

Chen, S., Chernozhukov, V., & Fernández-Val, I. (2019). Mastering panel metrics: Causal impact of democracy on growth. *AEA Papers and Proceedings*, *109*, 77–82. https://doi.org/10.1257/pandp.20191071

Chernozhukov, V., Kasahara, H., & Schrimpf, P. (2021). The association of opening k–12 schools with the spread of covid-19 in the United States: County-level panel data analysis. *Proceedings of the National Academy of Sciences*, *118*(42). https://doi.org/10.1073/pnas.2103420118

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Coccia, M. (2022). Optimal levels of vaccination to reduce covid-19 infected individuals and deaths: A global analysis. *Environmental Research*, *204*, 112314. https://doi.org/10.1016/j.envres.2021.112314

Colella, F., Lalive, R., Sakalli, S., & Thoenig, M. (2020). Acreg: Stata module to perform arbitrary correlation regression.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. https://doi.org/10.1016/s0304-4076(98)00084-0

Cot, C., Cacciapaglia, G., Islind, A. S., Óskarsdóttir, M., & Sannino, F. (2021). Impact of us vaccination strategy on covid-19 wave dynamics. *Scientific Reports*, *11*(1), 1–11. https://doi.org/10.1038/s41598-021-90539-2

Ertem, Z., Schechter-Perkins, E. M., Oster, E., van den Berg, P., Epshtein, I., Chaiyakunapruk, N., Wilson, F. A., Perencevich, E., Pettey, W. B., Branch-Elliman, W., & Nelson, R. E. (2021). The impact of school opening model on sars-cov-2 community incidence and mortality. *Nature Medicine*, *27*(12), 2120–2126. https://doi.org/10.1038/s41591-021-01563-8

Ferguson, N. M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunubá, Z., Cuomo-Dannenburg, G., Dighe, A., Dorigatti, I., Fu, H., Gaythorpe, K., Green, W., Hamlet, A., Hinsley, W., Okell, L. C., Elsland, S. V., … Ghani, A. C. (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce covid-19 mortality and healthcare demand.

Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J. W., Monod, M., Perez-Guzman, P. N., Schmit, N., Cilloni, L., Ainslie, K. E. C., Baguelin, M., Boonyasiri, A., Boyd, O., Cattarino, L., & Bhatt, S. (2020). Estimating the effects of non-pharmaceutical interventions on covid-19 in Europe. *Nature*, *584*(7820), 257–261. https://doi.org/10.1038/s41586-020-2405-7

Francis, A. I., Ghany, S., Gilkes, T., & Umakanthan, S. (2021). Review of covid-19 vaccine subtypes, efficacy and geographical distributions. *Postgraduate Medical Journal*, *98*(1159), 389–394. https://doi.org/10.1136/postgradmedj-2021-140654

Fuchs-Schundeln, N., Krueger, D., Ludwig, A., and Popova, I. (2020). *The long-term distributional and welfare effects of covid-19 school closures*. Technical report, National Bureau of Economic Research.

Fukumoto, K., McClean, C. T., & Nakagawa, K. (2021). No causal effect of school closures in Japan on the spread of covid-19 in spring 2020. *Nature medicine*, *27*(12), 2111–2119. https://doi.org/10.1038/s41591-021-01571-8

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8

Heath, P. T., Galiza, E. P., Baxter, D. N., Boffito, M., Browne, D., Burns, F., Chadwick, D. R., Clark, R., Cosgrove, C., Galloway, J., Goodman, A. L., Heer, A., Higham, A., Iyengar, S., Jamal, A., Jeanes, C., Kalra, P. A., Kyriakidou, C., McAuley, D. F., …, & Toback, S. (2021). Safety and efficacy of nvx-cov2373 covid-19 vaccine. *New England Journal of Medicine*, *385*(13), 1172–1183. https://doi.org/10.1056/nejmoa2107659

Isphording, I. E., Lipfert, M., & Pestel, N. (2021a). Does re-opening schools contribute to the spread of sars-cov-2? Evidence from staggered summer breaks in Germany. *Journal of Public Economics*, *198*, 104426. https://doi.org/10.1016/j.jpubeco.2021.104426

Isphording, I. E., Lipfert, M., & Pestel, N. (2021b). Schools under mandatory testing can mitigate the spread of SARS-CoV-2.

Istituto Superiore di Sanità (ISS). (2020). Dati indice riproduzione.

Istituto Superiore di Sanità (ISS). (2021). Prevalenza e distribuzione delle varianti di SARS-CoV-2 di interesse per la sanitàpubblica in Italia. dati 13 settembre 2021.

Keeling, M. J., Tildesley, M. J., Atkins, B. D., Penman, B., Southall, E., Guyver-Fletcher, G., Holmes, A., McKimm, H., Gorsich, E. E., Hill, E. M., & Dyson, L. (2021). The impact of school reopening on the spread of covid-19 in England. *Philosophical Transactions of the Royal Society B*, *376*(1829), 20200261. https://doi.org/10.1098/rstb.2020.0261

Kim, D., & Lee, Y. J. (2022). Vaccination strategies and transmission of covid-19: Evidence across advanced countries. *Journal of Health Economics*, *82*, 102589. https://doi.org/10.1016/j.jhealeco.2022.102589

Psacharopoulos, G., Collis, V., Patrinos, H. A., & Vegas, E. (2021). The covid-19 cost of school closures in earnings and income across the world. *Comparative Education Review*, *65*(2), 271–287. https://doi.org/10.1086/713540

Sato, Y., & Zenou, Y. (2015). How urbanization affect employment and social interactions. *European Economic Review*, *75*, 131–155. https://doi.org/10.1016/j.euroecorev.2015.01.011

Stantcheva, S. (2022). *Inequalities in the times of a pandemic*. Technical report, National Bureau of Economic Research.

Svaleryd, H., & Vlachos, J. (2022). Covid-19 and school closures.

Tiu, A., Susswein, Z., Merritt, A., & Bansal, S. (2021). *Characterizing the spatiotemporal heterogeneity of the covid-19 vaccination landscape*. MedRxiv.

van den Berg, P., Schechter-Perkins, E. M., Jack, R. S., Epshtein, I., Nelson, R., Oster, E., & Branch-Elliman, W. (2021). Effectiveness of 3 versus 6 ft of physical distancing for controlling spread of coronavirus disease 2019 among primary and secondary students and staff: A retrospective, statewide cohort study. *Clinical Infectious Diseases*, *73*(10), 1871–1878. https://doi.org/10.1093/cid/ciab230

Vlachos, J., Hertegård, E., & Svaleryd, H. B. (2021). The effects of school closures on sars-cov-2 among parents and teachers. *Proceedings of the National Academy of Sciences*, *118*(9). https://doi.org/10.1073/pnas.2020834118

Yoon, Y., Kim, K.-R., Park, H., Kim, S., & Kim, Y.-J. (2020). Stepwise school opening and an impact on the epidemiology of covid-19 in the children. *Journal of Korean Medical Science*, *35*(46). https://doi.org/10.3346/jkms.2020.35.e414

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How to cite this article: Amodio, E., Battisti, M., Gravina, A. F., Lavezzi, A. M., & Maggio, G. (2023). School-age vaccination, school openings and Covid-19 diffusion. *Health Economics*, *32*(5), 1084–1100. https://doi.org/10.1002/hec.4657

APPENDIX

A | Additional results

In this Appendix, we present some additional results. Table A1 contains the outcomes on heterogeneity of the effects estimated from Equation (2). Table A2 reports the results of the robustness tests from the estimation, respectively, of Equations (2) and (3).

TABLE A1 Heterogeneity: Covid-19 cases through the years and the role of vaccines.

	Dep. Var.: Yi = change in the growth rate of Covid-19 cases post school opening (2021-2020)					
	Low density population	High density population	Class-size < median	Class-size > median	Share of total vaccination < median	Share of total vaccination > median
Exposure to vaccines (age = 12–19, ν_1)	−0.152***	−0.054**	−0.098***	−0.140***	−0.165***	−0.119***
	(0.019)	(0.027)	(0.023)	(0.019)	(0.026)	(0.018)
Exposure to vaccines (age>19, ν_2)	−0.007*	0.003	−0.007	−0.011**	−0.015**	−0.007
	(0.004)	(0.010)	(0.007)	(0.004)	(0.006)	(0.004)
Change in the growth rate of Covid-19 cases pre-school opening (θ)	−0.053***	−0.050***	−0.063***	−0.047***	−0.079***	−0.028*
	(0.017)	(0.012)	(0.016)	(0.013)	(0.014)	(0.014)
Observations	15,992	16,538	11,635	21,010	16,460	17,011
R^2	0.091	0.144	0.140	0.085	0.101	0.071
Municipality fixed effects	Y	Y	Y	Y	Y	Y

Note: Standard errors are clustered at census area level.

***, **, and * denote significance at 1%, 5%, and 10%, respectively.

TABLE A2 Robustness tests.

	Estimation method				
	(1)	(2)	(3)	(4)	(5)
	Benchmark	ABC est.	Longer time window	AC corr.	PS
School opening (λ)	0.015***	0.012***	0.015***	0.014***	0.016***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
School opening X Year = 2021/22 (η)	−0.016***	−0.014***	−0.016***	−0.016***	−0.022***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Other controls	Y	Y	Y	Y	Y
Census area fixed effects	Y	Y	Y	Y	Y
Week dummies	Y	Y	Y	Y	Y
Observations	537,664	537,664	1,041,724	530,944	530,944
Number of census areas	33,604	33,604	33,604	33,184	33,184
R^2 within	0.21	-	0.21	0.21	0.21

Note: The table displays the results from a set of specifications conducted to test the robustness of the benchmark results reported in column 1. These tests include a first specification using the Analytical Biased corrected diff-in-diff estimation (column 2); a second specification considering and extended window of 8 weeks before and after the school opening (column 3); a third specification based on the method developed by Conley (1999); and a weighted specification using the methodology developed by Amodio et al. (2022). Standard errors are clustered at census area level.

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TABLE A3 Robustness test on the exposure specification.

	Estimation method				
	(1)	(2)	(3)	(4)	(5)
	Benchmark	**Alt. est.**	**Longer sample**	**1st dose**	**Benchmark 2**
Exposure to vaccines (age = 12–19, ν_1)	−0.141***	−0.678***	−0.105***	−0.059***	−0.141***
	(0.015)	(0.061)	(0.008)	(0.006)	(0.035)
Other controls	Y	Y	Y	Y	Y
Census area fixed effects	Y	Y	Y	Y	Y
Week dummies	Y	Y	Y	Y	Y
Number of census areas	32,490	33,184	32,490	32,490	32,490
R^2 within	0.09	0.21	0.14	0.09	0.09
Clustering of S.E. (census cell, CC, or municipality, M)	CC	CC	CC	CC	M

Note: The table reports the results from additional robustness tests on the definition of the dependent variable and and the number of doses. See Section 6.2 for a complete description of the table. Standard errors are clustered at census area level in (1)-(4), and at municipal level in (5).

***, **, and * denote significance at 1%, 5%, and 10%, respectively.

TABLE A4 Covid-19 cases, school opening and vaccines.

	Dep. Var.: Change ln of Covid-19			
	(1)	(2)	(3)	(4)
Specification	**Year = 2020/21**	**Year = 2021/22**	**Full sample**	**Full sample**
School opening (λ)	0.013***	0.001	0.015***	0.015***
	(0.002)	(0.002)	(0.001)	(0.002)
School opening X Year = 2021 (η)			−0.016***	−0.005
			(0.002)	(0.005)
School opening X Year = 2021/22 X ln of vaccinated (12–19)				−0.001**
				(0.001)
Δ ln Covid (lag) (ρ)	−0.561***	−0.436***	−0.454***	−0.454***
	(0.005)	(0.003)	(0.002)	(0.002)
ln Covid (t-3, β_3)	−0.038***	−0.077***	−0.099***	−0.099***
	(0.011)	(0.004)	(0.003)	(0.003)
ln Covid (t-4, β_4)	−0.008	−0.011***	−0.039***	−0.039***
	(0.011)	(0.004)	(0.003)	(0.003)
2020w34	−0.001		−0.001	−0.001
	(0.001)		(0.001)	(0.001)
2020w35	−0.002***		−0.002**	−0.002**
	(0.001)		(0.001)	(0.001)
2020w36	0.000		0.001	0.001
	(0.001)		(0.001)	(0.001)
2020w37	0.005***		0.006***	0.006***
	(0.001)		(0.001)	(0.001)
2020w38	0.018***		0.018***	0.018***
	(0.001)		(0.001)	(0.001)
2020w39	0.016***		0.014***	0.014***
	(0.002)		(0.002)	(0.002)
2020w40	0.034***		0.033***	0.033***
	(0.002)		(0.002)	(0.002)

(Continues)

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TABLE A4 (Continued)

Specification	Dep. Var.: Change ln of Covid-19 (1) Year = 2020/21	(2) Year = 2021/22	(3) Full sample	(4) Full sample
2021w34			0.029***	0.029***
			(0.002)	(0.002)
2021w35		−0.021***	0.008***	0.008***
		(0.003)	(0.002)	(0.002)
2021w36		−0.059***	−0.028***	−0.028***
		(0.003)	(0.002)	(0.002)
2021w37		−0.055***	−0.024***	−0.024***
		(0.002)	(0.002)	(0.002)
2021w38		−0.043***	−0.012***	−0.012***
		(0.002)	(0.002)	(0.002)
2021w39		−0.038***	−0.006***	−0.006***
		(0.002)	(0.002)	(0.002)
2021w40		−0.039***	−0.008***	−0.008***
		(0.002)	(0.001)	(0.001)
2021w41		−0.034***	−0.004***	−0.004***
		(0.002)	(0.001)	(0.001)
Test on school opening (prob. > 0)				
$\lambda_{2020/21} + \lambda_{2021/22} = 0$	-	-	0.23	-
Census area fixed effects	Y	Y	Y	Y
Week dummies	Y	Y	Y	Y
Year of lag var.	2020	2021	2020 & 2021	2020 & 2021
Observations	268,832	268,832	537,664	537,664
Number of census areas	33,604	33,604	33,604	33,604
R^2 within	0.22	0.22	0.21	0.21

Note: The table displays the results from Fixed-Effects estimates at census area level with weekly dummies. The dependent variable is the change in log of the weekly Covid-19 cases. The year 2021 dummy is added only in the interaction as it would be collinear with the week dummies. The indicator ln *of vaccinated* (12–19) denotes the natural logarithm of the share of the number of fully vaccinated individuals in school-age (12–19 years old) at the time of school opening at municipality level. This indicator is time invariant and it enters in the specification only in the interaction. Standard errors are clustered at census area level.

***, **, and * denote significance at 1%, 5%, and 10%, respectively.

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