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Causal impacts of teaching modality on U.S. COVID-19 spread in Fall 2020 semester

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Abstract

We study the impact of college reopening and teaching modality on county-level COVID-19 cases and deaths using the information of 1,076 U.S. colleges. We group the colleges by their teaching modes in the fall 2020 semester: in-person, online, and hybrid; and employ a logistic model to estimate the propensity scores for the three groups to minimize the pre-treatment imbalances of college and county-level covariates. We find that greater enrollment, endowment, individual mask policies, and fewer republican votes in the county are major predictors of adopting online or hybrid modes. Fixed effects before-after regression and treatment effects provide evidence that college reopening, especially with in-person teaching elements, increases daily new cases and deaths.

Introduction

The COVID-19 pandemic and its containment measures have unprecedentedly affected human health and economic activities (e.g., McKibbin and Fernando, 2020; Atkeson, 2020). Countries across the world have implemented partial or full business and school closures to mitigate the infection spread (Panovska-Griffiths et al., 2020; Di Domenico et al., 2020). Many U.S. colleges temporarily closed or switched to online in the spring semester, and over six out of ten colleges reopened in the fall semester with an in-person or a combination of in-person and online teaching plans (Gallagher and Palmer, 2020). College students mainly fall in the age cohort of 18 to 29 years, which has a lower death rate (0.4%) from COVID-19 (Wrighton and Lawrence, 2020), but a greater chance of socialization than the older age cohorts. Although colleges have taken different measures—including symptom screening, contact tracing, cleaning and disinfecting, and mandatory mask policies—there is a chance that reopening

colleges may spread the virus among faculty and staff serving students, and in the region around the college (Hubler and Hartocollis, 2020).

Fig 1 shows daily new COVID-19 cases grouped by college teaching modality in 30 days before and after the Fall reopening date. Median values across counties are plotted to remove the influence of extreme observations. Different colleges started the Fall semester on different dates from July to October. Fig 1 matches the reopening dates, and suggests that COVID-19 cases were falling before the Fall semester irrespective of teaching modality. Colleges teaching online are located in counties that had about 50 new COVID-19 cases per day before the college reopening date, but the numbers did not grow after reopening. However, counties where colleges taught in hybrid or in-person mode experienced a rise in cases. Thus, Fig 1 raises the question if, and to what extent, COVID- 19 cases grew in counties where colleges started the fall semester with some in-person instructional mode.

(Insert Figure 1 here)

Fig 1. Growth of COVID-19 cases by college teaching modality in Fall 2020 semester.

Note: Daily data of 1,076 colleges from July to October 2020. See the data section for details.

Source: Cases are obtained from the New York Times (2020), and teaching modalities were collected by authors from the respective college websites.

Given the substantial risk of infection spread from college campuses to the community, a timely policy question is whether colleges should continue with in-person classes or switch to online or hybrid mode. The current study applies a quasi-experimental approach to find the impacts of teaching modality on infection spread onto the neighboring areas. We combine college and county information to predict the

chance of a college adopting one of the three modes of teaching: in-person, online, and hybrid; and then estimate the effects of the decision on county COVID-19 outcomes. Results provide evidence that college reopenings, especially with in-person teaching elements, increase daily new cases and deaths. Most studies so far have looked into the impact of elementary and secondary school closure, optimal reopening plan, and teaching strategy (e.g., Di Domenico et al., 2020; Panovska-Griffiths et al., 2020; Gandolfi, 2020; Cohen et al., 2020). Walke, Honein, and Redfield (2020) discuss the possible issues of U.S. college reopening and the prevention measures required on campuses. In a study close to ours, Andersen et al. (2020) investigate college openings' association with cellphone-tracked human mobility and COVID-19 cases in the counties of the campuses. Their preliminary results (as of September 23rd, 2020) suggest that reopening increased county COVID-19 cases by 0.024 per thousand people, and no significant differences exist between online and in-person instructional modality. However, their study does not consider the fact that the choice of reopening and teaching modality is endogenous to observed cases. We use a matching method to re-weight the sample based on the college's probability of selecting an instructional mode. This approach also unravels the predictors of choosing a particular teaching mode. In addition, Andersen et al. (2020) collect start dates from the fall 2019 semester that may not represent the actual scenario in 2020 because some college opened early to finish the semester before thanksgiving vacation, whereas some colleges delayed opening or opened with an online mode waiting for cases to decrease.

Method

We are interested in finding the effects of teaching modality on two COVID-19 outcomes: (1) new daily COVID-19 cases per 100,000 people reported in the county, and (2) new COVID-19 related deaths per 100,000 people in the county. The impact of teaching modality is assessed on county-level outcomes

(and not on the college level) because students may spread the virus to non-students and immunocompromised people in the community, which is a pressing policy concern. First, we specify a simple before-after relationship between college reopening in the fall semester and the outcome as below,

$$Y_{it} = A_0 + \alpha(\text{Fall})_{it} + \beta X_{it} + \gamma t + A_i + e_{it} \quad (1)$$

where, Y_{it} is a COVID-19 outcome, $i = 1, \dots, N$, and $t = 1, \dots, T$ respectively indicate colleges and days, and A_0 is the intercept. Fall is a binary variable that takes value 1 when the college officially reopens for the fall 2020 semester, and zero for all previous dates. The vector X includes observed daily covariates such as percent of population who stayed at home, A_i is college fixed effects. Parameters to be estimated include α and β , and e_{it} stands for the error. Estimating α gives the average difference in Y_{it} between colleges that have reopened and colleges that have not, because different colleges reopened on different dates. We also control for the time variable t to capture the daily changes of the spread.

Then we measure the before-after effects by teaching modality, let the set {Online, Hybrid, In-person} denote the options a college can choose from. We re-specify the model as,

$$Y_{it} = A'_0 + \alpha_1(\text{Online})_{it} + \alpha_2(\text{Hybrid})_{it} + \alpha_3(\text{In-person})_{it} + \beta' X_{it} + \gamma' t + A'_i + e'_{it} \quad (2)$$

where, parameters α_1 , α_2 and α_3 show the effects of respective teaching modes on Y_{it} . The parameters in equations (1) and (2) are technically different, hence the prime (') sign, but have a similar interpretation. The intercept A'_0 represents the overall mean of pre-semester Y_{it} . We conduct F-tests to check if the effects statistically vary across teaching modes.

The next question of interest is whether switching from one mode to another, e.g., in-person to online, has an impact on the COVID-19 outcomes. We create three binary variables for pairwise comparison of teaching modalities: (1) in-person=1 and online=0, (2) hybrid=1 and online=0, and (3) in-person=1 and hybrid=0. We omit the third category while analyzing each pair; e.g., omit all colleges with hybrid

teaching modes while comparing in-person with online, and so on. The pairwise comparison explicitly focus on cross-mode effectiveness on COVID-19 outcomes in the following manner,

$$Y_{it} = A_0'' + \alpha''D + \beta''X_{it} + \gamma''t + A_i'' + \epsilon_{it}'' \quad (3)$$

where, D is a placeholder for one of the three dummy variables created above. For example, $D = 1$ when the college is teaching in-person and $D = 0$ when online for the first dummy variable. The causal effects of teaching modality on COVID-19 outcomes, shown by α'' , are identified if colleges were homogeneous and were randomly assigned a teaching mode (Barnow, Cain, and Goldberger, 1981). In practice, the treatment assignment is not random, because colleges choose the mode of teaching based on their distance education capacities, observed COVID-19 cases, and many other characteristics. The probability of adopting a teaching modality should considerably vary across colleges. Intuitively, if we could select two colleges with identical institutional and regional features, except one went in-person and the other online, we could measure the difference in COVID outcomes induced by the teaching modality. However, finding an identical match is hard due to the large number of features. A more practical way is to reduce the feature dimensions to one dimension—such as the probability of adopting in-person over online.

Rosenbaum and Rubin (1983, 1984) discuss propensity score matching (PSM) to adjust the probabilities for the differences in pre-treatment variables. A propensity score is the conditional probability of receiving the treatment given the pretreatment variables. In our context, the probabilities of selecting a teaching mode over another can be obtained from the following specification.

$$\begin{aligned} \{\text{In-person}_i = 1, \text{online} = 0\} &= f_1(\text{College features}, \text{Regional features}) \\ \{\text{Hybrid}_i = 1, \text{online} = 0\} &= f_2(\text{College features}, \text{Regional features}) \\ \{\text{In-person}_i = 1, \text{hybrid} = 0\} &= f_3(\text{College features}, \text{Regional features}) \end{aligned} \quad (4)$$

The probabilities of treatments generated from equation (4) are used to create weights that adjust the effects of treatments in estimating equation (3). For example, if a college has a high probability of

choosing online than in-person, greater weights are assigned on in-person than online during the estimation (Imbens, 2000; McCaffrey et al., 2013).

We estimate a logit model for PSM using cross-sectional data of college and county features. The predicted probabilities of adopting a teaching mode for each college are then inverted and used as weights in equation (3) to obtain the effect of choosing a teaching mode over the other. The sources of variation are colleges for the cross-section, and college times days for the panel.

Although it may take between several days or weeks to show symptoms or die after being infected, we do not use lag values of semester start dates because lagged time dummies are more relevant for a time-to-event estimate, e.g., how many days on average it takes for covid cases to increase after college reopening. Consistent with our research question, we compare the mean differences of outcomes in 30 days before and after college reopening—hence focusing on a change in the intercept of the model rather than the time. Since a definite incubation period is unknown, the number of lagged time variables is also unknown, and agnostically including many lags may create noise in the estimation due to heterogeneity of reporting across days.

Data and descriptive statistics

We collected characteristics of four-year and two-year undergraduate degree-granting colleges and universities from the National Center for Education Statistics (NCES, 2020). Most of the colleges available in the data are public or private non-profit. Data on teaching modality and the official start date of the fall 2020 semester were manually collected by authors from respective college websites¹. Over 90% of the colleges mentioned their latest teaching modality between June and September 2020.

¹ A list of colleges and their webpages are available on Syed Badruddoza's Github repository: <https://github.com/Badruddoza/College-websites>

Information for the remaining colleges was obtained from campus news or local news. Some examples of search phrases we used are, “XXX university fall 2020 covid information reopening plan new” or “XXX college restarts in-person class in fall 2020” or “XXX institute fall 2020 plan president announcement updated”. We categorize fall reopening plans into three types: (1) in-person, (2) online, and (3) hybrid. Colleges in the “in-person” group started Fall 2020 semester with face-to-face classes and open residence halls, and may include some online delivery materials; colleges in the “online” group primarily offered online classes with some exceptions for lab components and may have some students on campus; and colleges in the “hybrid” group either divided the class into online and in-person section, or switched the teaching mode on a rolling basis, or offered courses with both in-person and online access. County characteristics were extracted from the American Community Survey (ACS, 2020). Merging all these data sets eventually gives 1,076 colleges in 50 U.S. states and Washington D.C.

We obtain daily new COVID-19 cases and deaths at the county level from the New York Times (NYTimes, 2020). We also merged the data with individual mask policies in county and state from HealthData.gov (2020). Finally, information on county-level shares of republican votes in Presidential Election 2016 is included from the MIT Election Data and Science Lab (MIT, 2018) to take residents’ perception of COVID-19 risk into account (e.g., Tyson, 2020).

Table 1 provides variable descriptions and sources, and Table 2 presents summary statistics of variables used in PSM and panel FE. For the panel regression, we chose 61 days data for each college (30 days before, 30 days after and the semester start date). We created a time variable “days after fall reopening” that takes 0 on the reopening date, -30 on the first sampled date, and 30 on the last sampled date (for a visual representation, see Fig 1). The reason for arranging colleges by their reopening dates rather than using calendar dates is to avoid the aggregate trend of COVID-19. Since different colleges reopened on different dates, one can isolate the effect of reopening on COVID-19 from the aggregate trend. For an infectious disease that rapidly spread by day, using the same number

of dates before and after for all colleges create a balanced sample for comparison. The earliest reopening date in our sample is July 20th whereas the latest date is October 24th. We chose 30 days threshold because it gives COVID-19 enough time to appear in the outcomes, and because colleges might change teaching modes during the fall semester based on observed outcomes in the first few weeks, thus creating a reverse causality².

The panel regression controls for the percentage of county population that stayed home daily, collected from the Bureau of Transportation Statistics (BTS, 2020). Omitting stay-home makes the effects of a teaching mode on COVID-19 outcomes biased, because COVID-19 outcomes may increase if fewer people stay home regardless of campus reopening or teaching modality. Other variables are used to find the determinants of teaching modality and calculate the propensity scores. The PSM should only contain variables that are measured at baseline because variables measured at around the treatment may be influenced or modified by treatment (Austin, 2011). Therefore, we selected the determinants from the latest year available before the Fall 2020 semester. We also included total COVID-19 cases by the end of the Spring 2020 semester because it was the last regular semester that gave the college administration a signal about the disease situation in the community. Some studies find an association between temperature and COVID-19 spread (e.g., Livadiotis, 2020), so the average fall temperature was included in the model.

² For robustness, we also used 20 days before-after and 40 days before-after and found similar results (see the results section), which indicates that the findings are not sensitive to the threshold.

205 **Table 1. Variable description.**

(1)	(2)	(3)	(4)
Variable	Unit	Source	Details
Fall semester*	Binary	College websites	Takes 1 when the college officially started fall semester classes
Online*	Binary	College websites	Takes 1 if the college holds classes primarily online for Fall 2020, zero otherwise
Hybrid*	Binary	College websites	Takes 1 if the college adopts a combination of online and in-person modes for Fall 2020, zero otherwise
In-person*	Binary	College websites	Takes 1 if the college holds classes primarily in person for Fall 2020, zero otherwise
New cases*	Numeric	NYTimes (2020)	Daily new COVID-19 cases per 100,000 population in the county
New deaths*	Numeric	NYTimes (2020)	Daily new COVID-19 deaths per 100,000 population in the county
% stayed home*	Percentage	BTS (2020)	Percentage of county population that did not go outside home for longer than 10 minutes
Time*	Integer	Generated	Days after fall reopening (-30 to 30)
Enrollment	Count	NCES (2020)	Total student count in fall 2018 semester, including graduate and remote students
Cost of attendance	USD	NCES (2020)	Total price for in-state students living on campus for 2019-20
Endowment per student	USD	NCES (2020)	Endowment assets per FTE enrollment at the end of 2018
Student-faculty ratio	Ratio	NCES (2020)	Enrollment divided by total full-time instructional staff
Public	Binary	NCES (2020)	The institution is primarily funded by a state government
Total population	Count	ACS (2020)	Total population in the county where the college is located (2018)
Black population	Percentage	ACS (2020)	Percentage of African American population in the county (2018)
Household income	USD	ACS (2020)	Median real household income in 2018
Republican votes	Percentage	MIT (2018)	Percentage of votes for the Republican Party at the county level in Presidential election 2016
Mask ordinance	Binary	HealthData.gov (2020)	The county has an ongoing mandatory mask policy for individuals in public places
Cases in Spring 2020	Count	NYTimes (2020)	Total COVID-19 cases in the county by May 15, 2020
Fall temperature	Fahrenheit	NOAA (2021)	County mean temperature in September 2020

206 *Note:* Variables with asterisks vary with time (days) and are used in panel regression. Other variables are
207 used for PSM.

208 **Table 2. Summary statistics of variables used in matching.**

(1) Variable	(2) Online	(3) Hybrid	(4) In-person	(5) Overall
Time varying variables				
New cases/100,000 population	213.87 (461.93)	87.13 (252.93)	64.29 (202.37)	126.76 (341.71)
New deaths/100,000 population	4.40 (11.07)	1.80 (6.92)	1.17 (4.54)	2.55 (8.27)
Online				0.38 (0.48)
Hybrid				0.26 (0.44)
In-person				0.36 (0.48)
% stayed home	26.41 (4.06)	25.05 (4.33)	24.21 (4.00)	25.27 (4.22)
Time invariant variables				
Enrollment	8,828.61 (9,991.36)	6,307.21 (8,272.99)	4,417.95 (6,972.39)	6,580.85 (8,754.75)
Cost of attendance	44,980.83 (21,312.56)	46,178.28 (19,431.71)	41,089.31 (16,628.42)	43,757.31 (19,059.39)
Endowment per student	61,279.10 (347,471.23)	28,545.41 (62,887.43)	59,892.61 (367,714.37)	51,811.22 (307,016.55)
Student-faculty ratio	41.71 (30.23)	28.11 (22.71)	29.18 (25.53)	33.61 (27.44)
Public	0.60 (0.49)	0.38 (0.49)	0.33 (0.47)	0.44 (0.50)
Total population	1,578,217 (2,620,932)	616,050 (973,588)	444,525 (1,028,931)	917,566 (1,867,046)
Black population	14.57 (15.77)	13.68 (14.44)	11.89 (13.14)	13.37 (14.55)
Household income	64,587.54 (17,710.66)	59,805.99 (15,156.93)	56,796.75 (14,395.72)	60,526.88 (16,253.30)
Republican votes	38.94 (16.72)	46.09 (16.25)	52.97 (14.53)	45.86 (16.93)
Mask ordinance	0.86 (0.35)	0.80 (0.40)	0.71 (0.45)	0.79 (0.41)
Cases in Spring 2020	12,706.16 (23,007.05)	5,356.90 (10,396.52)	3,576.15 (10,177.45)	7,498.42 (16,800.38)
Fall temperature	72.37 (6.14)	71.38 (6.07)	70.89 (5.30)	71.58 (5.86)
Colleges	406	284	386	1,076
Time (days)	61	61	61	61
Observations (Colleges × Days)	24,766	17,324	23,546	65,636

Note: Standard deviations in parentheses. Table 1 provides variable description. Time-varying variables are used in panel regression whereas time-invariant variables are used as predictors teaching mode pairs in PSM.

A required condition for estimating treatment effects is distributional similarities of pre-treatment covariates across the treatment groups McCaffrey et al. (2013). Table 2 indicates considerable variation across treatment groups. The difference requires the use of PSM in our analysis. The calculation of propensity scores and testing for the distributional equality between the treatment and control group are explained in the result section.

Results

We begin with simple pre-post effects of college reopening under different teaching modes on COVID-19 cases and deaths using panel fixed-effects regression (equations 1 and 2). Table 3 shows that the daily new COVID-19 cases increased by about 0.780 cases per 100,000 population in the fall 2020 semester. The coefficient for daily new deaths is, however, statistically insignificant. The constant term shows the pre-semester average. When the fall semester dummy is categorized into online, hybrid, and in-person dummies, we find the post-reopening cases are 0.979 lower on average for colleges with online teaching mode, and 2.961 cases higher for colleges with in-person teaching mode than the pre-semester levels. The online dummy becomes insignificant for new deaths, but in-person dummy has a significant coefficient of 0.052. The hybrid dummy remains statistically insignificant for both cases and deaths. We conduct F-tests to check if the coefficients are equal (see the note below Table 3)—implying that the in-person coefficient is different than those of online and hybrid. Notice the negative coefficient

with time variable—indicating a drop in overall cases and deaths in the period. The coefficient with the percent of the population stayed home is also negative and significant.

Table 3. Before-after effects of college reopening.

	(1)	(2)	(3)	(4)
Variables	Daily new cases	Daily new deaths	Daily new cases	Daily new deaths
Fall semester	0.780*** (0.277)	0.014 (0.012)		
Online			-0.979*** (0.327)	0.002 (0.014)
Hybrid			0.352 (0.358)	-0.019 (0.016)
In-person			2.961*** (0.331)	0.052*** (0.014)
Time	-0.058*** (0.008)	-0.000 (0.000)	-0.058*** (0.008)	-0.000 (0.000)
% stayed home	-0.324*** (0.044)	-0.033*** (0.002)	-0.328*** (0.044)	-0.033*** (0.002)
Constant	22.003*** (1.093)	1.074*** (0.047)	22.116*** (1.092)	1.073*** (0.047)
Observations	65,636	65,636	65,636	65,636
R-squared	0.003	0.005	0.006	0.005
Colleges	1,076	1,076	1,076	1,076

Note: Fall semester takes 1 on and beyond the official reopening date, zero before the date. The constant represent pre-semester means. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We conduct F-tests to check the difference of the coefficients. For daily new cases (column 3), the F-statistic under the null hypothesis $H_0: \alpha_{online} - \alpha_{hybrid} = 0$ is 14.88***, $H_0: \alpha_{hybrid} - \alpha_{in person} = 0$ is 56.04***, and $H_0: \alpha_{online} - \alpha_{in person} = 0$ is 154.51***. For daily new deaths (column 4), the respective F statistics are 1.89, 22.06***, and 13.47***.

241 To calculate the probability of choosing a teaching mode over the other, we use a logistic regression.
242 The results in Table 4 show that colleges with greater enrollment are more likely to choose in-person
243 than online (column 1), and in-person than hybrid (column 3), holding other variables constant. A
244 percent increase in endowment per student decreases the log odds ratio of choosing in-person over
245 online by 0.288, and that of choosing hybrid over online by 0.253, given the other predictors. Public
246 colleges are less likely to choose in-person or hybrid modes as opposed to online. Similarly, on-going
247 mask ordinance has a negative association with going in-person, and more republican votes have a
248 positive association with choosing in-person or hybrid over online. To summarize, greater enrollment,
249 endowment per student, county population, fewer republican supporters in the county, and prevailing
250 individual mask ordinance are common predictors of adopting online or hybrid teaching modality over
251 in-person.

252 **Table 4. Logistic regression coefficients for pairwise comparison.**

Variables	(1) In-person=1 online=0	(2) Hybrid=1 online=0	(3) In-person=1 hybrid=0
Log enrollment	-0.407*** (0.149)	-0.0596 (0.153)	-0.303** (0.139)
Log cost of attendance	0.273 (0.544)	0.102 (0.555)	-0.0283 (0.526)
Log endowment per student	-0.288*** (0.104)	-0.253** (0.110)	-0.0623 (0.0946)
Log student-faculty ratio	-0.531 (0.337)	-0.970** (0.385)	0.315 (0.336)
Public=1, 0 otherwise	-1.212** (0.509)	-0.926* (0.522)	-0.438 (0.500)
Log total population	-0.478*** (0.178)	-0.422** (0.179)	-0.0748 (0.162)
Black population (%)	0.0112 (0.0109)	-0.000172 (0.00993)	0.0176 (0.0108)
Log household income	0.238 (0.578)	0.131 (0.542)	0.158 (0.560)
Republican votes (%)	0.0568*** (0.0113)	0.0243** (0.00987)	0.0285*** (0.0103)
Mask ordinance=1, 0 otherwise	-0.563** (0.286)	-0.197 (0.300)	-0.431* (0.240)
Log cases in Spring 2020	0.162 (0.119)	0.171 (0.121)	-0.0407 (0.106)
Fall temperature	-0.0162 (0.0238)	0.00587 (0.0211)	-0.0287 (0.0223)
Constant	6.328 (8.404)	6.368 (8.407)	2.889 (7.971)

Observations (colleges)	532	456	538
Pseudo R-squared	0.231	0.075	0.082

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The third category is omitted from the sample for each pairwise comparison. We use log forms of predictors that have few points larger than the rest of the data to reduce the influence of extreme values on coefficient estimates.

We use the logit model to calculate the propensity scores for each college. The scores need to be sufficiently similar across groups for causal estimation. Fig 2 compares the distributions of the propensity scores using box plots and Kolmogorov-Smirnov (KS) statistics, before and after trimming observations with too small or too large scores (McCaffrey et al., 2013). Based on the box plot and KS statistics, we fail to reject the null hypothesis of distributional equality after trimming the scores, shown by the “after” column in Fig 2. That is, we use PSM to create a smaller sample such that the treatment and control teaching mode in each pair is equally likely to be chosen by a college. We now utilize the sample to estimate the causal effects of teaching modality on COVID-19 cases and deaths.

(insert Figure 2 here)

Fig 2. Overlap assessment of propensity scores by pairs of teaching modes.

Note: Horizontal axis shows observed values of treatment, the vertical axis shows the estimated propensity scores. Box plots provide visual similarities of propensity scores’ distribution across teaching modes, whereas Kolmogorov-Smirnov statistics match two unknown distributions under the null of equality (e.g., p-values close to zero raises concern that the distributions are different). The boxes show the interquartile range of the score, the dividing lines in the boxes represent the medians, whereas the upper and lower whiskers show the upper and lower quartile. The vertical line from top to bottom covers from the expected maximum (1.5 times of interquartile range above the third quartile) to the

minimum value (1.5 times of the interquartile range below the first quartile). The dots represent the
 observed scores that are outside the expected range, hence are possible outliers. We trim too low and
 too high values to increase the similarity of distributions. For each binary dependent variable, the left
 column shows the scores before trimming, and the right column shows the scores after trimming.

Table 5 presents the regression results using trimmed and PSM-weighted samples, and allows for a
 cross-mode comparison. The dependent variables (1) daily new COVID-19 cases per 100,000 people and
 (2) daily new COVID-19 deaths per 100,000 people do not have autocorrelation. The adjusted t statistics
 from Levin, Lin, and Chu (2002) unit-root tests are $-85,8056$ and $-1.2e+02$ respectively, both significant
 at 0.01%. The average treatment effect of in-person teaching mode as compared to online is 3.846—
 implying that a typical college that went in-person has about 4 new cases more per 100,000 population
 per day than a similar college that went online. However, the same statement cannot be made for
 deaths as the coefficient is not statistically significant. The hybrid-online difference exhibits an
 interesting pattern—hybrid colleges have 0.593 new cases but 0.055 fewer deaths. A possible
 explanation is that the colleges that already had many cases reopened with online mode, and might had
 a spillover to the fall semester. It is also possible that many students chose online when offered a
 combination (hybrid) of online and in-person—thus contributing to a mixed result. Finally, colleges that
 reopened with in-person mode had about 4 cases and 0.027 deaths more than similar colleges with
 hybrid mode per 100,000 population per day. Among other variables, the consistent negative
 association between the percent of people stayed home and COVID-19 outcomes is noticeable.

The results in Table 5 are based on 61 days data (30 days before reopening, 30 days after, plus the
 reopening date). To check the robustness of the results, we repeated the analysis using 41 days data (20
 days before and after), and 81 days data (40 days before and after). Tables 5A and 5B summarize the
 findings. The pattern is similar across the threshold specifications.

298 **Table 5. Impact of teaching modality on daily COVID-19 outcomes.**

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	New cases	New deaths	New cases	New deaths	New cases	New deaths
In-person=1, online=0	3.846*** (0.555)	0.00275 (0.0145)				
Hybrid=1, online=0			0.593* (0.316)	-0.0552*** (0.0102)		
In-person=1, hybrid=0					4.075*** (0.520)	0.0272** (0.0132)
Time (days)	-0.00636 (0.0253)	-0.00129 (0.000796)	0.0170 (0.0160)	-0.00102** (0.000512)	-0.00651 (0.0249)	8.61e-05 (0.000728)
% stayed home	-1.189*** (0.104)	-0.0212*** (0.00452)	-0.674*** (0.0382)	-0.0212*** (0.00179)	-0.781*** (0.0852)	-0.0124*** (0.00450)
Constant	42.18*** (3.141)	0.777*** (0.126)	28.84*** (1.190)	0.818*** (0.0558)	30.55*** (2.252)	0.488*** (0.118)
Colleges	211	211	412	412	158	158
Observations	6,541	6,541	12,772	12,772	4,898	4,898
R-squared	0.041	0.015	0.028	0.030	0.036	0.009

299 *Note:* Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. “New cases” means daily
300 new COVID-19 cases per 100,000 people and “New deaths” means daily new COVID-19 deaths per
301 100,000 people. Observations are trimmed and weighted using propensity scores to increase the
302 distributional similarity across the treatment and control group. The dataset is a panel of colleges over
303 61 days (30 days before reopening, 30 days after, and the reopening date).

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Table 5A. Impact of teaching modality on daily COVID-19 outcomes with 20 days before after reopening data.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	New cases	New deaths	New cases	New deaths	New cases	New deaths
In-person=1, online=0	3.725*** (0.726)	-0.00420 (0.0177)				
Hybrid=1, online=0			0.112 (0.398)	-0.0735*** (0.0133)		
In-person=1, hybrid=0					4.341*** (0.696)	0.0422*** (0.0160)
Time (days)	0.0772* (0.0461)	-0.00224* (0.00132)	0.0307 (0.0304)	-0.000647 (0.000919)	0.0584 (0.0499)	0.000882 (0.00142)
% stayed home	-1.300*** (0.137)	-0.0212*** (0.00592)	-0.719*** (0.0497)	-0.0232*** (0.00236)	-0.844*** (0.116)	-0.0117* (0.00613)
Constant	44.48*** (3.970)	0.786*** (0.168)	30.17*** (1.469)	0.876*** (0.0722)	31.56*** (2.932)	0.456*** (0.165)
Colleges	211	211	412	412	158	158
Observations	4,431	4,431	8,652	8,652	3,318	3,318
R-squared	0.042	0.016	0.030	0.035	0.036	0.008

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. “New cases” means daily new COVID-19 cases per 100,000 people and “New deaths” means daily new COVID-19 deaths per 100,000 people. Observations are trimmed and weighted using propensity scores to increase the distributional similarity across treatment and control group. The dataset is a panel of colleges over 41 days (20 days before reopening, 20 days after, and the reopening date).

Table 5B. Impact of teaching modality on daily COVID-19 outcomes with 40 days before after reopening data.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	New cases	New deaths	New cases	New deaths	New cases	New deaths
In-person=1, online=0	3.797*** (0.466)	0.00986 (0.0132)				
Hybrid=1, online=0			0.636** (0.277)	-0.0468*** (0.00877)		
In-person=1, hybrid=0					3.344*** (0.436)	0.0327** (0.0148)
Time (days)	0.00540 (0.0188)	-0.000782 (0.000569)	0.0410*** (0.0110)	-0.000726** (0.000350)	0.0144 (0.0177)	0.000171 (0.000628)
% stayed home	-1.005*** (0.100)	-0.0202*** (0.00360)	-0.654*** (0.0336)	-0.0202*** (0.00148)	-0.614*** (0.0906)	-0.0132*** (0.00358)
Constant	37.16*** (2.987)	0.740*** (0.100)	28.01*** (1.049)	0.784*** (0.0467)	26.29*** (2.443)	0.506*** (0.0918)
Colleges	211	211	412	412	158	158
Observations	8,651	8,651	16,892	16,892	6,478	6,478
R-squared	0.033	0.012	0.027	0.026	0.025	0.007

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. “New cases” means daily new COVID-19 cases per 100,000 people and “New deaths” means daily new COVID-19 deaths per 100,000 people. Observations are trimmed and weighted using propensity scores to increase the distributional similarity across the treatment and control groups. The dataset is a panel of colleges over 81 days (40 days before reopening, 40 days after, and the reopening date).

Concluding remarks and implications

Our findings have several implications for higher education and health policy. First, results from the logit model suggest that colleges with smaller endowments per student are less likely to choose online over in-person teaching mode, after controlling for other factors. Moreover, the treatment effects show adopting an in-person mode instead of an online or hybrid mode may increase COVID-19 cases. Therefore, colleges with small endowments need special policy attention to combat a disease-induced crisis.

Second, the before-after regression suggests that campus reopening has a positive impact on COVID-19 cases, and both new cases and new deaths are significantly higher for colleges teaching in person. The treatment effects regression indicates that the damage could have been partially mitigated with an initiative from the colleges by increasing distance education elements in classes.

Finally, counties with more republican votes in Presidential Election 2016 were less likely to choose online or hybrid modes over in-person, *ceteris paribus*. The finding indicates that political affiliation might play a role in the containment of COVID-19.

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Teaching modes

- Online
- Hybrid
- In-person