Estimating the Effects of Regulating University Face-to-Face Lectures on the Spread of COVID-19: Evidence from Japan

Michinao Okachi (michinao.okachi@waka.c.u-tokyo.ac.jp)
University of Tokyo
Haewon Youn
University of Tokyo

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Estimating the Effects of Regulating University Face-to-Face Lectures on the Spread of COVID-19: Evidence from Japan

Michinao Okachi, Haewon Youn

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Abstract

Universities are the only institutions that have conducted most lectures online during the prolonged COVID-19 pandemic, but no researcher has analyzed the effects of nonface-to-face lectures on containing the spread of the novel coronavirus. This study is the first attempt to estimate these effects. Applying a multiple-event study negative binomial regression model, we find that changing the ratio of online lectures had only slight effects on the numbers of COVID-19 infections among university students. For example, if universities regulate almost all lectures in-person from lectures consisting of more than a half of in-person style, the number of student infections declined by 5.5 per 10,000 students between seven weeks prior and posterior to the change. Other lecture style changes show milder differences than this. Considering these results, minimizing or restricting face-to-face lectures does not appear to be particularly effective for preventing the spread of the coronavirus.

Key words: COVID-19, University lecture style, Multiple event study, Negative binomial panel regression

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Michinao Okachi is an associate professor at Graduate School of Arts and Sciences, the University of Tokyo (E-mail: michinao.okachi@waka.c.u-tokyo.ac.jp), and a visiting associate professor at Research Center for Policy Design, Tohoku University.

Haewon Youn is a Ph.D. student at Graduate School of Arts and Sciences, the University of Tokyo. (E-mail: haewon0831@gmail.com)

1 Introduction

Since the outbreak of the COVID-19 pandemic in Wuhan China in 2019, people around the world have been affected by this serious crisis. Prior to the development of the vaccines, we had few measures to prevent the spread of this novel coronavirus (SARS-CoV-2). Individually, people wore masks and practiced physical distancing, and many governments declared states of emergency and regulated flows of people at a societal level. The Japanese government had been also announcing state-of-emergency and pre-emergency measures several times in epicenters such as Tokyo and Osaka by February 2022.[1] Figure 1 depicts the changes in the numbers of weekly infections in Japan within and outside of the declared states of emergency and pre-emergency measures in Tokyo.

Under the new COVID conditions, schools from kindergartens to universities have also needed to take measures not to spread the coronavirus. For example, all public schools under the first state of emergency decided to delay the commencement of the new school term in April 2020. After the end of this state of emergency, schools from kindergartens to high schools (i.e., K–12) started face-to-face lectures with adequate measures such as wearing masks and staggered attendance. Subsequently, the Japanese government did not request that public K–12 schools take strong measures such as closing schools or holding classes only online even during the second through the fourth states of emergency. However, almost all universities in Japan have been restricting face-to-face lectures to a certain degree since the outbreak of the pandemic in Japan.[2] University students have shown frustration with not having had sufficient conventional face-to-face lectures for about two years.[3] We believe it will be beneficial to investigate whether testing students' patience with restrictive measures in fact helps contain the spread of coronavirus.

In this paper, we studied the effects of three different university lecture styles on the number of infections among university students: face-to-face and online lectures with less than half online; face-to-face and online with more than half online; and nearly all or all lectures online. The empirical strategy of our analysis is the event study model, often called

[1] There are several differences between the state of emergency and pre-emergency measures. For example, under the former, a governor of each prefecture has a right to close restaurants, but under the latter, can only order restaurants to shorten their hours of operation.

[2] According to a survey conducted by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) in October 2020, about a half of surveyed universities were conducting less than 50% of their lectures face-to-face even not under the state of emergency.

[3] For instance, a student at Meisei University sued the university in June 2021 for a refund of half of their tuition as well as compensation for mental distress.

a difference-in-difference (DID) event study model or dynamic DID model. These models can estimate the dynamic effects of events prior and posterior to occurrences of events of interest. A growing number of researchers are adopting the event study model with respect to economics.[1] Researchers used the term "event study" in fewer than 1% of papers published by the top five economics journals[4] in the 1990s, but the rate increased steadily and reached about 4% in 2017.

However, whereas most prior studies suppose a single event, we need to assume multiple events for this study because universities frequently change their lecture styles. According to researchers on one study, the "multiple-event study model is more challenging than in the single-event case,"[2] and only a limited number of researchers have studied multiple-event panel analysis.[1],[3] Later in this paper, we carefully explain the treatment of multiple events. In addition, many prior event study models assume Gaussian distribution on the error term, but the numbers of infections at each university are count data that are distributed close to zero. Thus, instead of Gaussian distribution, we assume negative binomial distribution for the number of student infections, which is a dependent variable in our model.

The results of our analysis are as follows. For most university lecture style changes (four of six combinations), we identified subtle differences in the numbers of student infections, fewer than 5 per 10,000 students between 7 weeks prior and posterior to these changes. The largest infection difference came with the change from less than half of lectures online to almost all or all lectures online, but that difference was only -5.5 per 10,000 students between the same durations. The judgment of whether this value is high or low is quite subjective, but it is safe to say that less than 0.1% of students affected by the change in lecture style is not a large number.

Next, we also analyzed the infection changes between semesters and breaks. The results report that the start of long breaks from any three kinds of lecture styles induces a higher level of infections. Thus, on the contrary to the start of long breaks, we expected fewer new infections at the start of a new semester. However, this case also brought more infections unless universities conducted lectures almost always or entirely online. This asymmetricity is consistent with a prior conclusion that the increase in the number of infections by moderation is larger than its decline by regulation.[4] We confirmed the validity of these baseline results with two robustness analyses of different controls omitting outliers.

[4] *Econometrica, Journal of Political Economy, Quarterly Journal of Economics, American Economic Review, and Review of Economic Studies*

The contributions of this paper can be summarized as follows. First, to the best of our knowledge, this is the first examination of a causal relationship between university lecture styles and university student infections. University education styles under the COVID-19 pandemic have been quite controversial especially in Japan because despite the fact that universities have been taking the strictest measures among all educational institutions, we do not know if what university students have endured was worth the efforts to contain the spread of coronavirus. This paper can provide the information to judge whether universities should limit or moderate their lecture styles. Second, instead of a conventional single-event study model, we successfully applied a more complex multiple-event study model, a methodology that is available for other analyses because many events occur multiple times such as natural disasters or fiscal policy changes. We expect that researchers will be able to apply this method to wider areas of studies.

This paper is organized as follows. In Section 2, we briefly review the literature on COVID-19, which addresses behavioral restriction effects and the event study model, and then present the significance of our study with respect to previous studies. In Section 3, we provide our estimation model. In Section 4, we explain the data for our analysis. Section 5 shows our baseline results, and Section 6 provides additional results of robustness analyses. Finally, Section 7 presents concluding remarks and discusses limits of our analyses.

2 Literature review

Our paper is related to two major research strands, COVID-19 and the event study model.[5] First, there is a growing body of literature on the relationships between COVID-19 infections and measures to contain the spread of coronavirus such as the varying effectiveness of lockdown measures internationally.[6] For instance, some Asian countries such as China, Taiwan, and South Korea had over 90% reduction in new cases by adopting lockdown measures at the beginning of this pandemic, but new cases in Italy, Spain, and the United States remained persistently high.[6] Some researchers identified limited impacts of local mobility restriction on the spread of the coronavirus,[7],[8] but others determined that relaxing regulations can send a signal that moving around is no longer dangerous, which can increase infections again.[4]

Today, a growing number of researchers are studying the effectiveness of nonpharmaceutical measures to cope with COVID-19 because of its significant and ongoing impacts on societies, education, economies, etc., and some literature sheds light on the effectiveness of school closures as one such measure. Some found that COVID-19 infections increased when students attended in-person school, but the magnitude of infections was small[9]; others, however, identified a gradual but substantial increase in spread with the return of in-person school.[10] Our paper differs from these, especially from earlier studies of educational institutions, in that we focus on lectures at universities, probably the most controversial of all educational institutions, and we attempt to measure impacts of lecture style as a measure of ratios of face-to-face lectures rather than measuring the simple closed versus open dichotomy that many prior researchers have chosen to focus on.

In terms of literature related to the methodology of the event study model, researchers in many socioeconomic areas have applied the model because of the straightforwardness of its underlying econometrics and intuitive graphs.[1] Recent research examples of using event study models have included studying the relationships between parents' family planning and childhood economic resources and analyzing the effects of primary care reform on ambulatory care conditions.[11],[12] In one event study model investigation, closures of assembly plants led to high opioid overdose mortality,[13] and investigators on another study reported a spillover effect of parents' high access to university on their children's years of education attainment.[14]

However, even though a growing number of researchers are adopting event study models, most have focused on a single-event study. Single-event study models are more convenient to use than multiple-event study models, but they cannot handle social phenomena in which events occur more than one time. We hope that our model specification with the multiple-event study will contribute to analyses of not only COVID-19 but other social phenomena that also occur as multiple events.

3 Model

In the field of epidemiology, infection cases are usually regarded as count data, and the data related to epidemiology often display highly skewed distributions.[5],[15] In these cases, conventional linear regression models with Gaussian-distributed error terms are inappropriate for empirical estimations of epidemiological studies; thus, researchers usually adopt count regression models for these studies. Additionally, the data for this study are multidimensional: cross-sectional data on the universities and time-series data for estimated COVID-19 infections at each university. Thus, we adopt a panel count regression model for this estimation.

Let $y_{u,t}$ be a panel count variable of each university's student COVID-19 infections, where u and t are each university and time, respectively. Then, the estimation model can be written as

$$E(y_{u,t}|x_{u,t}) = \exp(\beta' x_{u,t}) \tag{1}$$

where $x_{u,t}$ is a vector of independent variables and β is a vector of corresponding coefficients. We suppose an exponential regression given that count data usually change exponentially. The canonical regression models for count data analyses often specify a Poisson regression model as

$$P[Y = y_{u,t}|x_{u,t}] = \frac{\exp(-\lambda_{u,t})\lambda_{u,t}^{y_{u,t}}}{\Gamma(1 + y_{u,t})} \tag{2}$$

with $\lambda_{u,t} = E(y_{u,t}|x_{u,t})$. This specification of Poisson distribution derives identical conditional mean and variance. However, the distribution of COVID-19 cases at each university (count data) is highly skewed from the assumption of Poisson distribution because these two values are greatly different.[5,6] Instead of Poisson regressions, the negative binomial distribution is also widely adopted for count regression models, derived by adding the error term into equation (1) as

$$E(y_{u,t}|\mathbf{x}_{u,t}, \varepsilon_{u,t}) = \exp(\beta' \mathbf{x}_{u,t} + \varepsilon_{u,t}) = \lambda_{u,t} g_{u,t} \tag{3}$$

where $g_{u,t}$ is one parameter gamma distribution as $g_{u,t} \sim Gamma(\theta, \theta)$. This distribution takes 1 and $1/\theta$ for the values of average and variance, respectively. After integrating out this distribution from the joint distribution, we obtain the probability mass function of negative binomial distribution as

$$P[Y = y_{u,t}|x_{u,t}] = \frac{\Gamma(\theta + y_{u,t})}{\Gamma(1 + y_{u,t})\Gamma(\theta)} \left(\frac{\lambda_{u,t}}{\theta + \lambda_{u,t}}\right)^{y_{u,t}} \left(\frac{\theta}{\theta + \lambda_{u,t}}\right)^{\theta} \tag{4}$$

Unlike in the Poisson distribution, here, the mean and variance are derived as $\lambda_{u,t}$ and

[5] The average and variance of COVID-19 cases in our analysis are 3.0 and 94.4 respectively.

[6] The Poisson distribution is appropriate if each event occurs independently. However, the occurrence of COVID-19 cases is sticky, depending on past cases.

$\lambda_{u,t}[1+\lambda_{u,t}/\theta]$, respectively; thus, the negative binomial distribution can treat high-dispersion cases. We compare these two distributions with both the Akaike information criterion and the Bayesian information criterion[7] and confirm the validity of assuming the negative binomial distribution over the Poisson distribution.

We estimate the model with maximum log-likelihood and estimate the maximum log-likelihood parameters by taking the derivatives of the log-likelihood function with respect to the parameter θ and coefficients β.

Next, we explain the concrete specification in equation (3). We adopt an event study model to analyze the effects of university lecture style changes on COVID-19 cases among university students. Although most event study models assume a one-time event,[16],[17] we assume multiple events because universities change their lecture styles multiple times, including around long breaks. Thus, following prior research,[3] we formulate a multiple-event study model as

$$y_{u,t}=\exp\left(\sum_{\pi}\sum_{j\geq\underline{j}}^{\overline{j}}\alpha^{\pi,j}b_{u,t}^{\pi,j}+X'_{u,t}\Gamma+\mu_u+\theta_t+\log U+\varepsilon_{u,t}\right) \tag{5}$$

The first term in the parenthesis of exponential indicates the dynamic treatment effect of changing university lecture styles, $\alpha^{\pi,j}$ is its parameter, and $b_{u,t}^{\pi,j}$ represents binned event indicator[8] expressed as

$$b_{u,t}^{\pi,j}=\begin{cases}\sum_{s=-\infty}^{\underline{j}} d_{u,t-s}^{\pi} & \text{if } j=\underline{j} \quad .\\ d_{u,t-j}^{\pi} & \text{if } \underline{j}+1\leq j\leq\overline{j}-1\\ \sum_{s=\overline{j}}^{\infty} d_{u,t-s}^{\pi} & \text{if } j=\overline{j} \quad .\end{cases} \tag{6}$$

The subscript π shows lecture style changes. We categorize lecture styles including long breaks into one of four types: (1) hybrid of face-to-face and online, less than half of lectures

[7]We estimate parameters using the maximum likelihood (ML) method. However, the ML method can often cause the problem of multicollinearity under the assumption of Poisson distribution. Thus, instead of ML method, we estimate the model of Poisson distribution with Poisson pseudo-maximum likelihood estimation.

[8]The Supplementary Information explains the details of this binned event indicator $b_{u,t}^{\pi,j}$ with concrete examples.

online; (2) hybrid of face-to-face and online, more than half of lectures online; (3) almost online or online only; and (4) long breaks.[9] We explain the detailed classification of each lecture style in the next section. Following our categorization, there are 12 ($= {}_4P_2$) potential lecture style changes. The subscript j represents time periods prior to ($j < 0$), at the week of ($j = 0$), and posterior to ($j > 0$) the time of lecture style changes. A negative (positive) value of j indicates a lag (lead) of event occurrence. This subscript is regarded as a time integer variable, taking $\underline{j} \leq j \leq \overline{j}$ where $\underline{j}$ and $\overline{j}$ are endpoints of the event window, defined as the duration of the effects of a particular event. Endpoints of event window $\underline{j}$ and $\overline{j}$ accumulate prior and posterior effects beyond period $\underline{j}$ and $\overline{j}$, respectively. These two indicators represent long-lasting effects prior and posterior to the events. The indicator $d_{u,t}^{\pi}$ is expressed as

$$d_{u,t}^{\pi} = \begin{cases} 1 & \text{if } e_u^{\pi} = t \\ 0 & \text{otherwise} \end{cases} \quad . \tag{7}$$

where a variable e_u^{π} is the week of university u's lecture style changes as π. That is, if u changes its lecture style as π at time t, $d_{u,t}^{\pi}$ takes unity, and it takes zero otherwise. Thus, following equation (6), if an identical lecture style changes more than one time, the event window endpoints are more than one. For example, if a university changes its lecture style two times from less than half to more than half of lectures online, the indicator $b_{u,t}^{\pi,j}$ takes the value of two $\overline{j}$ weeks after the second lecture style change. With respect to the length of the event time window, these are usually assumed to be very long.[3] However, universities change their lecture styles frequently as is shown in Figure 2, so coefficients of the indicator that occur far away from a lecture style change might correspond to different lecture styles. Thus, it would be appropriate to consider shorter event windows than those in other conventional event study models.

Meanwhile, of course, if we take a too-short event time window, we cannot estimate long time effects of lecture style changes. Thus, we assume the event time window as eight weeks, setting $\underline{j} \leq j \leq \overline{j}$ to -8 and 8, respectively.[10] We exclude the coefficient of the indicator at the time of lecture style change (i.e., $j = 0$) from both lag and lead indicators because

[9] We excluded the conventional face-to-face lecture style from π because none of the universities we investigated had held only conventional face-to-face lectures since the outbreak of COVID-19 in Japan.

[10] Ziedan et al. (2020) set the same event window, assuming lag indicators from -8 to -1 weeks and lead indicators from 0 to 6 weeks. They include the timing of the event occurrence week as one of the lead indicators.

there exist some time lags between lecture style change and onset of coronavirus infection. According to the US Centers for Disease Control and Prevention (CDC), the incubation period of COVID-19 between exposure and onset is estimated to be four or five days in the medium term; therefore, the effects of lecture style change would not be apparent at the week of the change. Given this, we set the event time window as 17 weeks, excluding the week of lecture style change from lag and posterior indicators.

The second term is a vector of university-specific and time-varying controls: infection rate, vaccination rate, and three dummies: state of emergency, travel subsidies, and the omicron variant in each prefecture where a university was located.[11] Because some variables could cause the problem of multicollinearity, we calculate the variance inflation factor, and all variables show factors less than 2. Therefore, we conclude that multicollinearity is absent from the model. The third term μ_u and fourth term θ_t are fixed effects of university and time, respectively. The fifth term $\log U$ represents the number of students exposed; we normalize the number of university cases per number of students at each university because of the proportional relationship between these two terms. The last term $\varepsilon_{u,t}$ is the error term, corresponding to one parameter gamma distribution in equation (3).

4 Data

First, we explain general characteristics of all the data, including our method of selecting universities for this study; then, we provide the detailed explanation of each variable. We utilized the following data for our analysis: both COVID-19 cases and lecture style changes at each university, total infection rate, vaccination rate, and the dummy variables of state of emergency, travel subsidies, and the omicron variant. The frequency of data collection was weekly, and the range was from the third week of February 2020 (2/17–2/23), when all the universities we investigated were on spring vacation, to the fourth week of January 2022 (1/24–1/30). As Table 1 shows, we selected 38 Japanese universities; the table shows the numbers of students at each university as of 2016.

We collected the university data by accessing two years of school announcements at each

[11] Instead of assumptions of dummy variables, we consider that these variables are controlled into the first term of the event indicator as cross terms. If it had been possible, we could have extracted pure effects of these variables around the timing of lecture style change with this model. However, the number of coefficients that we need to estimate would have increased dramatically, which would have reduced the statistical significance. Therefore, we avoided assuming cross terms.

university's website. However, it is of course almost impossible to investigate all universities in Japan, and therefore, we restricted our investigation to universities that had more than 8,000 students because a university's infection rate per student would look greater if an infection cluster broke out at a smaller university. Meanwhile, since most of larger universities are located in large cities, such as Tokyo and Osaka, individual school student infection rates would reflect not Japan as a whole. Thus, to ensure diversity within this focus on larger universities, we relaxed the threshold for the number of students to include national and public universities located near their prefectural government offices. Next, we selected universities that disclosed weekly or daily cases because we intended to standardize our data on a weekly basis. With these considerations in mind, we selected 38 universities in total.[12] Next, we explain the details of each variable.

Number of infections of each university

Universities across Japan took many different approaches to disclosing their COVID-19 infection case numbers. Thus, we standardized the infection numbers as follows. First, we included not only student infections but also cases among academic faculty and staff members because most universities do not disclose infection cases by individual in order to protect privacy. Lecture styles, however, also affect faculty and other staff members as well as students, so it would be more comprehensive measurements to include their infections.[13]

Second, we did not distinguish where students were infected. Although it seems likely that many students would have been infected outside of their campuses, most universities did not disclose detailed information about where infections were acquired in part because of the difficulty in identifying where and how people were infected but also, again, because of privacy concerns. However, we anticipated that there would be a correlation between university lecture style and off-campus infections because students likely go out with their friends after lectures in-person. Thus, we concluded it was not necessary to try to distinguish places of students' infections further.

Third, although we would like to select only the timing of students' confirmation of infections, we include the timing that universities recognize their students' infections because some universities do not disclose the former timing. We considered it likely that there were

[12] We excluded a few universities because their campuses were scattered across several prefectures.

[13] Meanwhile, we excluded the numbers of infected faculty and staff members who worked at their university hospitals if universities specified them because these infections were not related to lecture styles.

lags of several days between these two timings but that we would still capture them accurately because we were only collecting weekly data sets and in many cases, the two would have occurred within the same week.

Fourth, some universities disclosed infection numbers over a duration of several days rather than daily or on specific days; in those cases, we calculated average infections per day and added these to the weekly infections. For example, if a university disclosed 12 student infections in 3 days and the first two days were in a different week from the last day, then we counted 8 student infections in the former week and 4 in the latter week. Figure 3 shows the weekly numbers of infections. More than half of the total sample reported no infection, although this number declined as the number of infections increased.

Lecture style

As we explained in the previous section, we categorized four types of lecture styles including long breaks; however, there is no uniform categorization of lecture styles among universities, and thus, we set our own categories. The first style we identified was face-to-face and online lectures where fewer than half of lectures were online; a typical example of this case was that universities were providing face-to-face lectures for most classes but allowing for online lectures if administrative staff or faculty members did not want to participate in-person. The second style mixed face-to-face and online but with more than half of the lectures conducted online; in most cases in this category, the universities used face-to-face lectures primarily for their smaller classes.

The third category of lecture style we investigated was almost or entirely online, where lectures were face-to-face only for exercises and/or experiments or were not in-person at all; we combined these two because there were few differences in their findings. The final category of lecture type we studied was long breaks. The prime reason for setting this category was, of course, to examine the changes in infection case numbers between semesters and breaks.[14] However, another reason was that setting this category explicitly allowed us to separate the impacts of breaks from the impacts of changes in lecture style during the semester.[15]

Figure 2 shows the lecture style changes that took place at the 38 universities we selected. At the beginning of the new Japanese school year in April 2020, the majority of universities

[14] The duration of winter break, from the end of December to the beginning of January, is about one week. Thus, we excluded this break from the category of long breaks. We considered that the changes in infection numbers during this period would be captured by the time fixed effect.

[15] Note that we excluded the style of conventional face-to-face lectures because no university held only in-person lectures during our study period between February 2020 and January 2022.

postponed starting the new semester or began with lectures either mostly or entirely online. Even though the infection situation had improved from June, most of universities had been taking almost online lectures. However, after the summer break, more than half of the universities took the hybrid of face-to-face and online because scientists began to understand the virus's low infectivity to younger people at that time. Since then, Japan experienced several waves of high and low infection periods, and corresponding to them, universities relaxed or regulated the degree of in-person lectures. At the beginning of January 2022, the omicron variant caused infection numbers to rise again, and universities began restricting their face-to-face lectures before the start of the long breaks that begin in February. As the figure shows, the degree of restrictions on face-to-face lectures is varied among universities. This high variation of lecture style among Japanese universities allows us to examine the natural experiment, distinguishing the treatment and control groups.

Control Variables

As control variables, we adopt the following five: infection rate, vaccination rate, and three dummies: state of emergency, travel subsidies, and omicron variant. First, we extract the daily number of COVID-19 infections by prefecture from the Japan Broadcasting Corporation. Then, we convert this number to weekly data and divide it by the population of each prefecture; we took the population data from the statistics bureau of Japan. Next, we obtain the number of individuals who received two vaccine doses; although special workers such as health care workers received the vaccine earlier than others, vaccines for the general population began in the first week of May 2021, and we obtained these data from the government chief information officers' portal. We also divide the number of dual-vaccinated people by the population of each prefecture to derive the vaccination rate.

Third, we apply a dummy variable that takes unity when the government declares a state of emergency, including pre-emergency measures.[16] Fourth, we also include a travel subsidy dummy variable because this policy had the effect of driving up infection numbers including among university students. Under this policy, the government provided travel subsidies from July 22 to December 28, 2020, for all residents in Japan except residents of Tokyo and travelers whose destination was Tokyo. The aim of this subsidy was to boost the demand for tourism, and beginning on October 1, 2020, the subsidy was applied to all residents in

[16] We also estimate the model that excludes pre-emergency measurements from the state of emergency dummy. However, this result differs little from the baseline result.

Japan.

Finally, many novel coronavirus variants have emerged worldwide since SARS-CoV-2 was discovered in Wuhan China. The early variants showed weaker infectivity in younger people than in the elderly or others, which resulted in lower infection rates among young people. However, newer variants are showing higher infectivity even among younger people; indeed, the omicron variant, the dominant variant at the beginning of 2022, showed a dramatically high infection rate among younger people. Thus, we include the omicron variant as a dummy control variable. This variable takes unity after the first case of omicron variant infection was detected in a prefecture where one of the study universities is located. We took these data from the Ministry of Health, Labour and Welfare.

5 Result

Figure 4 shows the dynamic graphical results of the effects of lecture style changes on the numbers of university student infections during semesters (Less: hybrid, fewer than half of lectures online, More: hybrid, at least half of lectures online but not most lectures, Almost: all or nearly all lectures online). The graphs in the six panels in Figure 4 correspond to combinations of changes in these three lecture style. For example, Figure 4(a) "Less to More" presents the changes in student infection numbers as the universities changed from less than half to more than half of lectures online; the horizontal axis shows weeks since the lecture style change. The zero week represents the time of a lecture style change, and *Pri* and *Pos* indicate the average of long-lasting infection differences of more than 7 weeks prior and posterior to a single lecture style change. The dependent variable of the estimated equation (5) is an exponential regression, so we take the natural logarithm for the coefficients to derive the proportions of the variables' effects. Then, we standardize these coefficients as the deviations from the average weekly infections per 10,000 students at all sampled universities. Red dots represent estimated means, and bars indicate 95% confidence intervals.

To graphically understand the posterior effects of lecture style changes, we set the average value from seven weeks to one week prior to the style change to zero. We mainly compare seven weeks of cumulative infection numbers prior and posterior to the lecture style change, but we also provide three weeks of cases for short-term comparison. We select three weeks because the immediate impact of lecture style change would be reflected within three weeks;

according to the CDC, symptoms appear within 14 days of exposure to the virus.

As we have explained, Figure 4(a) represents the effect of lecture style change from less than half to more than half of lectures online. The number of infections increased three weeks before the lecture style change, and universities would have made any decisions to regulate the degree of face-to-face lectures at that time. Some universities notified students of their intended changes to face-to-face lectures before classes resumed and the changes took effect to warn students to refrain from their riskier behaviors. Such announcements would have halted the increase in infections before the lecture style change, and indeed, the figure shows that the number of infections declined until two weeks after that change with some fluctuations.

However, this warning and lecture style change were not sufficient to contain the spread of the virus, and the number of infections increased three weeks after the change. It is possible that the mild regulatory reinforcement had a temporary effect but that the sense of caution eased with the passage of time. Although the cumulative infection differences from three weeks prior to the lecture style change to three weeks posterior to that change are about -4.2 per 10,000 students, this cumulative difference between seven weeks is positive, 2.2 per 10,000 students.[17]

Figure 4(b) reports the lecture style change from "Less to Almost." Similar to the findings in Figure 4(a), the numbers of infections declined before this change. However, unlike in the previous figure, the numbers of infections remained low even three weeks after the change; this finding implies that the spread of the virus can be contained longer if universities substantially limit face-to-face lectures. The cumulative differences between three weeks and seven weeks prior and posterior to lecture style changes are about -4.5 and -5.5 per 10,000 students, respectively.

Figure 4(c) provides the results for moving from more to fewer online lectures. This policy relaxed the limits on face-to-face lectures, so as expected, the numbers of infections show an increasing trend following this change with some fluctuations. The cumulative differences for three weeks and seven weeks are about 3.1 and 5.2 per 10,000 students, respectively.

Figure 4(d) presents the case of universities' moving from more lectures online to all or nearly all lectures online. As Figure 4(a) and (b) show, the infection numbers increase before

[17] Because the total number of university students in Japan was about 2.973 million in 2019, it is roughly estimated that the total number of university student infections will increase by 300 students if a lecture style change increases the number of infections by one person per 10,000.

the lecture style change, indicating that universities began limiting face-to-face lectures as the infection situation worsened. However, the infection decline following this change is subtle, cumulative differences of about -2.1 and -0.5 per 10,000 students at three weeks and seven weeks, respectively.

Figure 4(e) displays the change from "Almost to Less." Before the universities relaxed their restrictions on face-to-face lectures, infection numbers were decreasing consistently from five weeks prior to the change because of the effects of the strict measures. Then, the decreasing tendency in numbers of infections stopped at the week of this lecture style change, although this relaxing of restrictions did not greatly increase the number of infections. We consider that this occurred because the numbers of infected students declined substantially during the period of heavy restrictions on face-to-face lectures and it lowered the infection risk associated with the subsequent relaxation of restrictions: The cumulative difference between three weeks prior and posterior to lecture style change is about 0.4 per 10,000 students, and seven weeks difference prior and posterior to is -3.7 per 10,000 students.

Figure 4(f) shows the case of universities' moving from nearly all lectures online to most lectures online. We observed the announcement effect in this case in that the number of infections began to increase before this lecture style change: Universities announced their intentions to relax the restrictions on in-person lectures, and students took the announcements as opportunities to engage in riskier behaviors such as going out with friends. Indeed, after the lecture style change, the infection numbers were higher than before. The cumulative differences between three weeks and seven weeks prior and posterior to lecture style change are both about 4.2 per 10,000 students.

We also show the numbers of long-lasting infections of more than seven weeks prior and posterior to the lecture style change, which are expressed as *Pri* and *Pos* in the figures, but there are no significant differences between these two numbers. Although Figure 4(a) shows a difference between Pri and Pos of about 1.3 infections per 10,000 students, all other panels in the figure show differences of less than 1. This implies that lecture style changes did not have long-lasting effects on the numbers of new coronavirus infections among Japanese university students. Table 2(a) summarizes the results of lecture style change on numbers of infections. We list our expected results and estimation results for the differences in both three weeks and seven weeks of cumulative infections between prior and posterior to lecture style changes. We expected that student infections would decline the more universities restricted face-to-face lectures, and the empirical results for three weeks of cumulative infections supported this proposition. However, we found cumulative results at seven weeks that were inconsistent with our expectations in two cases, from "Less to More" and from "Almost to Less." Even so, however, the cumulative differences were not large.

Figure 5 shows the changes in numbers of infections between semesters and long breaks. For instance, Figure 5(a), "Less to Break," shows the case numbers during the period from the lecture style with fewer than 50% of lectures online to the start of a long break, a period that encompasses two opposite effects on the spread of infections. On the one hand, students had fewer opportunities to meet their friends regularly on campus, which should have reduced infections, but on the other, students had more opportunities to engage in extracurricular activities, which had the effect of increasing the number of infections. Judging from the estimation results in Figure 5(a), the latter effect outweighed the former: University student infection counts increased at the start of a long breaks.

Next, Figure 5(b) shows the infection numbers from a period of more than half of lectures online to a long break. Similar to the previous result, the start of long breaks induced the spread of the virus among university students, although to a lesser degree than when most lectures before the break had been in-person. Figure 5(c) presents the findings for the shift from almost all lectures online to a break: Although the numbers of infections did not change significantly in the four weeks after the start of a long break, they increased five weeks after. This finding suggests that the effects of the strict regulations held for some time but that students on break ultimately could not stay at home for long periods and instead went out to socialize.

Figure 5(d) to (f) show the changes in infection numbers from breaks to new semesters. Figure 5(d) and (e), respectively, present the case numbers at the beginning of a semester with under half of lectures online and at least half of lectures online; in both cases, infection numbers were higher at the start of a new semester than a long break. Interestingly, these results appear to conflict with the findings for Figure 5(a) "Less to Break" and (b) "More to Break." Because these two panels show high infection numbers at the starts of long breaks, numbers be low in Figure 5(d) and (e), but instead, they are higher when the new semesters begin.

This disparity results from the asymmetric impacts of restrictions and moderations. As prior researchers established, the degree of decrease in the number of infections by restriction is lower than the degree of their increase by moderation: Figure 5(d) and (e) indicate that the incremental effects of university students' return to school outweighed the decremental effect of their decreases in extracurricular activities during breaks.[4]

Figure 5(f) presents the infection numbers for when students returned from a break to lectures that were almost entirely or entirely online. In these cases, students were rarely on campus or engaging in extracurricular activities, and as we expected, infection numbers in these cases were low. In terms of the long-lasting infection gaps, that is, the differences between Pri and Pos, all values were less than 1 in all figures. That is, similar to when the lecture style changed during a semester, university student infection numbers were not significantly affected by either the beginning or the end of a long break.

Table 2(b) summarizes both expected and estimation results for the effects of breaks and of the ends and beginnings of semesters. As we have explained, infections increased with all combinations except for "Break to Almost," findings that suggest that regardless of breaks or semesters, starting something new can activate people to go out and lead to increasing numbers of infections. However, with strict limits on face-to-face lectures at the start of a new semester, universities can contain the spread of the virus to a certain degree.

Finally, Table 3 shows our raw estimation results for the coefficients and standard errors of the independent variables: lecture style change. Our estimation model is taken by exponential as defined in equation (5), so the threshold to increase or decrease the rate of infections is one. Thus, a coefficient higher than one increases the number of university student infections, and vice versa. In the table, the coefficients do not necessarily show statistical significance. This is partly because students are infected not only in classrooms but in other places as well such as at home or during nonschool activities. Therefore, even though we controlled for other variables such as infection and vaccination rates, it was impossible to extract the pure effects of lecture style change.

The other reason Table 3 findings do not necessarily show significance is the multiple lags between infection, confirmation, and disclosure. For instance, students varied in when they informed their schools of their symptoms, and some universities only disclosed when they recognized a student's infection as COVID-19, not necessarily when the infection had been confirmed. These lags affected the findings of low statistical significance and wider 95% confidence intervals. However, we do believe it possible to grasp the overall tendency of whether university infections are spreading or abating and also the approximate magnitudes of infections.

Next, the control variables showed varied statistical significance: Vaccination rate and the emergency and travel subsidy dummies were significant, but infection rate and the omicron variant dummy were not. First, the coefficient of vaccination rate was lower than one, meaning that university student infection numbers declined as more people were vaccinated, which was consistent with our expectation. However, in contrast with our expectations, the emergency and travel subsidy dummies were higher and lower than one, respectively. Regarding the former variable, we considered that states of emergency would not be powerful enough to contain the spread of virus among students, rather it merely reflects the serious infection situations. Similarly, the travel subsidy dummy reflected low infection situations among students. Infection rate was statistically insignificant because of the lesser infectivity of earlier variants in young people, and the statistical insignificance of omicron variant dummy was attributed to few examples. Both coefficients and statistical significance of all control variables are robust under different control models.

To sum up, universities' changes in their lecture styles drove only subtle effects on infections among their student bodies. Even when universities dramatically restricted face-to-face lectures, the numbers of student infections only decreased by 5.5 per 10,000 students between seven weeks prior and seven weeks posterior to the change. The transitions between semesters and long breaks were associated with slight increases in infection numbers unless universities strictly limited face-to-face lectures.

6 Robustness

To confirm the validity of the baseline results that we provide in the previous section, we conduct two robustness analyses; Figure 6 shows their results. Note that we only provide the results for changes from fewer than half of lectures online to nearly all lectures online to avoid the redundancy of explaining other robustness results; the effects of other changes are explained in the Supplementary Information. The first robustness check is the estimation without any control variables. Figure 6(a) shows the baseline result for comparison, and Figure 6(b) provides the case of no controls. We do not observe a significant difference between the two figures: the cumulative number of infected students at seven weeks after the lecture style change declined by 5.5 per 10,000 students in the baseline estimation of

Figure 6(a), and the number in Figure 6(b) is 4.8 per 10,000 students.

Next, we also examine the robustness of omitting outliers because data with cluster cases may disturb the estimation of underlying effects of lecture style changes. We calculate outliers of students' infections under the assumption of negative binomial distribution,[18] and derive that the thresholds of omitting number of student infections per week at significance of 0.01 and 0.05 are 39 and 18 per 10,000 students, respectively. These thresholds shift in proportion to the number of students at each university. For example, the significance threshold of 0.01 for Meiji University is 130 infections in a week because the university has 33,310 students, whereas the 0.01 threshold for Mie University, which has 7,252 students, is 28 infections. The number of omitted samples at significance of 0.01 is 72 out of 3,876 total samples, and the number at 0.05 is 152. Figure 6(c) and (d) show estimation results for excluding outliers at significance of 0.01 and 0.05, respectively. We anticipated that omitting samples would show milder dispersion of the number of infections, but both figures show similar results to the baseline. The seven weeks cumulative differences at 0.01 and 0.05 significance are -6.9 and -4.8, respectively. In summary, we obtained similar results to the baseline following our robustness analyses, and we consider our findings to validate the results of the baseline estimation from these two robustness analyses.

7 Conclusion

In this paper, we examined the effects of university lecture style changes on the spread of COVID-19 among students. The methodology of estimation is the panel multiple-event study model with an assumption of negative binomial distribution for the number of student infections.

Our analysis shows subtle effects of most university lecture style changes on the number of students' infections, with fewer than 5 infections per 10,000 students between seven weeks prior and posterior to these lecture style changes; even the largest infection difference was only about 5.5 infections per 10,000 students between the same duration. We also estimated the numbers of infection changes between semesters and long breaks, and we found high infection numbers at the beginnings of long breaks irrespective of the lecture style prior to the break, although infections also increased when a new semester began with more face-to-face lectures. This asymmetric effect confirms the prior research finding that the factors that increase COVID-19 infections outperform the factors that would decrease infections. Only when universities began new semesters with strictly limited face-to-face lectures did student infections decline.

There are several limitations to our analysis. First, the model did not specify the duration of a given lecture style after a university changed it, and it was at least sometimes the case that styles changed within one event time window, for instance within the seven weeks since the last change. Other universities did not change their lecture styles frequently, but we treated all lecture style changes uniformly. This was justified because the purpose of this study was not to test any effects of the duration of lecture style change on infection rates but rather to quantify the comprehensive effect of a lecture style change on the number of infected students. Thus, if a particular university changed its lecture styles frequently, our analysis reflects its short duration and also captures the effect of the next lecture style on the number of student infections.

Second, we based our analyses on the original novel coronavirus and its early variants, which were established in early research as having weak infectivity in young people, but much more infectious variants have emerged since then. In Japan, the infection rate among younger generations remained substantially low until March 2021. However, since the alpha variant, which first emerged in the U.K., hit Japan in April 2021, the number of infections among young people has been increasing. Although the omicron variant has been controlled, the number of college students infected might be underestimated because the variant has only recently begun to spread, and we did not fully cover the period affected by this variant.

Lastly, we offer comments for university administrators. With this paper, we do not recommend relaxing versus restricting face-to-face lectures; rather, we merely provide results of an empirical analysis. However, our analyses revealed only subtle increases in the numbers of university student infections with increases in the ratios of face-to-face lectures.

Recent researches have found correlations between quarantine and self-isolation and the deterioration of children's and adolescents' mental health.[19],[20] Even though infection situation deteriorates again in the future, it would be better for university students to take alternative measurements such as hybrid-flexible lectures rather than online only. We hope that universities can use our findings to consider the student perspective in designing future lectures.

References

[1] Schmidheiny, K. & Siegloch, S. On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization (ZEW Discussion Paper 20-017, 2020).

[2] Askitas, N., Tatsiramos, K. & Verheyden, B. Estimating worldwide effects of non-pharmaceutical interventions on COVID-19 incidence and population mobility patterns using a multiple-event study. *Scientific Reports*, 11, 1972 (2021).

[3] Ziedan, E., Simon, K. I. & Wing, C. Effects of state COVID-19 closure policy on NON-COVID-19 health care utilization DOI 10.3386/w27621 (NBER Working Paper 27621, 2020).

[4] Glaeser, E. L., Jin, G. Z., Leyden, B. T. & Luca, M. Learning from deregulation: The asymmetric impact of lockdown and reopening on risky behavior during COVID-19 (NBER Working Paper 27650, 2020).

[5] Selvin, S. *Statistical Analysis of Epidemiologic Data* (Oxford University Press, 2004).

[6] Chaudhry, R., Dranitsaris, G., Mubashir, T., Bartoszko, J. & Riazi, S. A country level analysis measuring the impact of government actions, country preparedness and socioeconomic factors on COVID-19 mortality and related health outcomes. *EClinicalMedicine*, 25, 100464 (2020).

[7] Goolsbee, A. & Syverson, C. Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of Public Economics*, 193, 104311 (2021). https://doi.org/10.1016/j.jpubeco.2020.104311.

[8] Gupta, S., Nguyen, T. D., Rojas, F. L., Raman, S., Lee, B., Bento, A., Simon, K. I. & Wing, C. Tracking public and private responses to the COVID-19 epidemic: Evidence from state and local government actions (NBER Working Paper 27027, 2020).

[9] Bravata, D., Cantor, J., Sood, N. & Whaley, C. Back to school: The effect of school visits during COVID-19 on COVID-19 transmission (NBER Working Paper 28645, 2021).

[10] Courtemanche, C. J., Le, A. H., Yelowitz, A. & Zimmer, R. School reopenings, mobility, and COVID-19 spread: Evidence from Texas (NBER Working Paper 28753, 2021).

[11] Bailey, M. J., Malkova, O. & McLaren, Z. M. Does access to family planning increase children's opportunities? Evidence from the War on Poverty and the early years of Title X. *Journal of Human Resources*, 54, 825–856 (2019). DOI: 10.3368/jhr.54.4.1216-8401R1.

[12] Dimitrovova, K., Perelman, J. & Serrano-Alarcon, M. Effect of a national primary care reform on avoidable hospital admissions (2000–2015): A difference-in-difference analysis, *Social Science & Medicine*, 252, 112908 (2020). DOI: 10.1016/j.socscimed.2020.112908.

[13] Venkataramani, A. S., Bair, E. F., O'Brien, R. L. & Tsai, A. C. Association between automotive assembly plant closures and opioid overdose mortality in the United States: A difference-in-differences analysis. *JAMA Internal Medicine*, 180, 254–262 (2020). DOI: 10.1001/jamainternmed.2019.5686.

[14] Suhonen, T. & Karhunen, H. The intergenerational effects of parental higher education: Evidence from changes in university accessibility. *Journal of Public Economics*, 176, 195–217 (2019). https://doi.org/10.1016/j.jpubeco.2019.07.001.

[15] Gonzalez-Blanks, A., Bridgewater, J. M. & Yates, T. M. Statistical approaches for highly skewed data: Evaluating relations between maltreatment and young adults' non-suicidal self-injury. *Journal of Clinical Child & Adolescent Psychology*, 49, 1–15 (2020). DOI: 10.1080/15374416.2020.1724543.

[16] Simon, D. Does early life exposure to cigarette smoke permanently harm childhood welfare? Evidence from cigarette tax hikes. *American Economic Journal: Applied Economics*, 8, 128–159 (2016). DOI: 10.1257/app.20150476.

[17] Fuest, C., Peichl, A. & Siegloch, S. Do higher corporate taxes reduce wages? Micro evidence from Germany. *American Economic Review*, 108, 393–418 (2018). DOI: 10.1257/aer.20130570.

[18] Davies, L., & Gather, U. The identification of multiple outliers. *Journal of the American Statistical Association*, 88, 782–792 (1993).

[19] Liu, S., Yang, L., Zhang, C., Xiang, Y. T., Liu, Z., Hu, S. & Zhang, B. Online Mental Health Services in China During the COVID-19 Outbreak. *The Lancet Psychiatry*, 7, e17-e18 (2020). DOI: 10.1016/S2215-0366(20)30077-8.

[20] Tang, S., Xiang, M., Cheung, T. & Xiang, Y. T. Mental health and its correlates among children and adolescents during COVID-19 school closure: The importance of parent-child discussion. *Journal of Affective Disorders*, 279, 353–360 (2021). DOI: 10.1016/j.jad.2020.10.016.

Tables and Figures

Table 1: Study Universities and Numbers of Students.

National and Public University		Private University			
Kyoto Univ.	22,657	Meiji Univ.	33,310	Aichi Shukutoku Univ.	9,155
Kyushu Univ.	18,660	Doshisha Univ.	29,459	Dokkyo Univ.	8,790
Tohoku Univ.	17,849	Ryukoku Univ.	19,896	Mukogawa Women's Univ.	8,726
Hokkaido Univ.	17,414	Senshu Univ.	19,406	Hokkai-Gakuen Univ.	8,406
Nagoya Univ.	15,852	Meijo Univ.	15,412	Shibaura Inst. of Tech.	8,395
Hiroshima Univ.	15,292	Chukyo Univ.	13,117	Osaka Sangyo Univ.	8,381
Chiba Univ.	14,163	Kyoto Sangyo Univ.	12,996	Seinan Gakuin Univ.	8,315
Niigata Univ.	12,456	Tohoku Gakuin Univ.	11,569	Soka Univ.	8,020
Kanazawa Univ.	10,236	Chubu Univ.	11,266		
Shizuoka Univ.	10,222	Kobe Gakuin Univ.	10,877		
Kumamoto Univ.	10,083	Rissho Univ.	10,520		
Tokyo Metropolitan Univ.	9,185	Aichi Univ.	10,207		
Saitama Univ.	8,579	Chiba Inst. of Tech.	9,763		
Univ. of the Ryukyus	8,184	Nanzan Univ.	9,672		
Mie Univ.	7,252	Konan Univ.	9,256		

Notes 1: The right column of each university name represents the number of students in 2016

Notes 2: There is no well-organized data about the number of university students. We obtain this data from an article published by Toyo Keizai Inc., which is a publisher specializing in economics and businesses. The company collected these data with questionnaire survey.

Source: Toyo Keizai Inc.

Table 2: Expected and Estimation Results.

(a) During Semesters

From	Less		More		Almost	
To	More	Almost	Less	Almost	Less	More
Expected	-	+	+	-	+	+
Estimation (3 Weeks)	-	+	+	-	+	+
Estimation (7 Weeks)	+	-	+	-	-	+

(b) Breaks and Semesters

From	Less	More	Almost	Break		
To	Break			Less	More	Almost
Expected	+/-	+/-	+	-/+	-/+	-
Estimation (3 Weeks)	+	+	+	+	+	-
Estimation (7 Weeks)	+	+	+	+	+	-

Notes: "Expected" means our expected positive or negative effects of lecture style changes on the number of infections. "Estimation 3 Weeks" represents the cumulative infection differences from 3 weeks prior to the lecture style change to 3 weeks posterior to that change. "Estimation 7 Weeks" indicates the cumulative infection differences from 7 weeks prior to the lecture style change to 7 weeks posterior to that change.

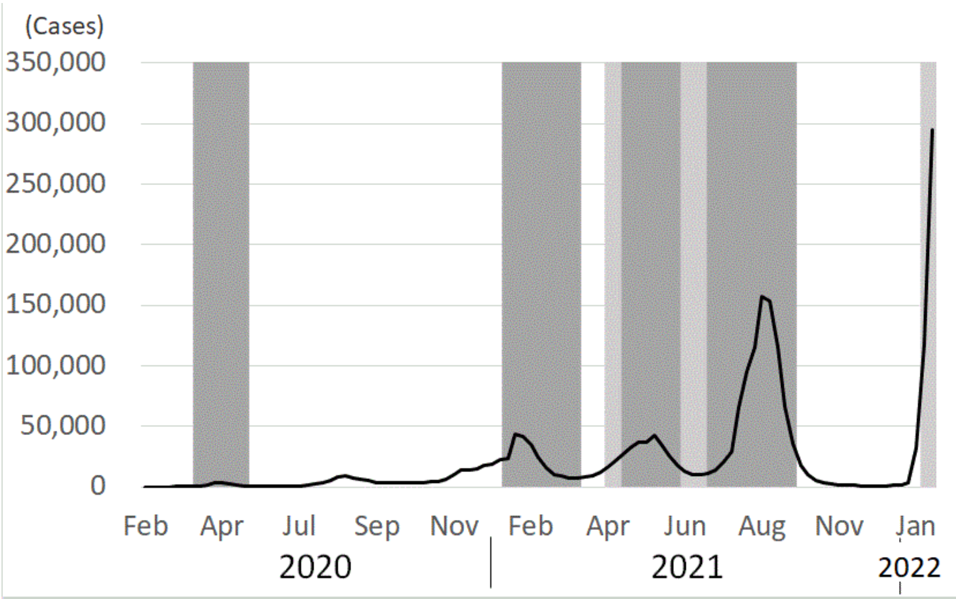
Table 3: Summary Statistics.

Indicator	During Semesters						Breaks and Semesters					
	(a) Less to More	(b) Less to Almost	(c) More to Less	(d) More to Almost	(e) Almost to Less	(f) Almost to More	(g) Less to Break	(h) More to Break	(i) Almost to Break	(j) Break to Less	(k) Break to More	(l) Break to Almost
Prior	0.7871	0.9455	1.0079	1.0581	1.3168	0.9415	1.3197	1.6161	1.1516	1.0488	0.6502	0.7347
	(0.1284)	(0.1755)	(0.144327)	(0.142409)	(0.240787)	(0.124325)	(0.474747)	(0.44504)*	(0.291757)	(0.186957)	(0.081)***	(0.139114)
Lag 7	0.6311	0.7298	1.1982	0.5469	1.2288	1.2910	0.8886	1.4028	1.3392	0.8508	0.5917	1.0751
	(0.291)	(0.3651)	(0.316228)	(0.209417)	(0.34629)	(0.294993)	(0.415261)	(0.489832)	(0.452754)	(0.249241)	(0.1505)**	(0.286119)
Lag 6	1.0552	0.6450	1.2293	0.7388	1.6065	0.6453	0.7596	1.1706	1.3707	0.6520	0.8200	1.0770
	(0.4298)	(0.2983)	(0.327476)	(0.25851)	(0.43166)*	(0.1592)*	(0.370258)	(0.399846)	(0.44512)	(0.213316)	(0.216868)	(0.307886)
Lag 5	0.6807	0.9335	1.1278	0.7168	2.2137	0.7626	0.7266	1.0462	0.9610	0.8198	0.8718	1.1815
	(0.2812)	(0.4009)	(0.318761)	(0.233153)	(0.581)***	(0.194741)	(0.334104)	(0.35105)	(0.318918)	(0.272919)	(0.246248)	(0.321567)
Lag 4	0.5276	1.6985	0.8208	0.7677	2.0692	0.7369	0.8525	1.1258	0.9668	0.9219	1.0229	1.1601
	(0.2128)	(0.567)	(0.259548)	(0.252492)	(0.5916)**	(0.210337)	(0.366927)	(0.359688)	(0.295908)	(0.302568)	(0.289124)	(0.334423)
Lag 3	1.7637	1.7597	0.7646	1.0458	1.5057	0.4338	1.1942	1.2660	0.8858	1.1291	0.8134	1.3403
	(0.4891)**	(0.5745)*	(0.27725)	(0.283308)	(0.505795)	(0.144)**	(0.507978)	(0.398015)	(0.265562)	(0.385203)	(0.263084)	(0.402836)
Lag 2	1.5105	2.2268	1.1267	1.5684	0.9870	0.9869	1.1773	1.3830	0.8479	0.8304	1.0503	1.2989
	(0.3599)*	(0.7075)**	(0.394247)	(0.3501)**	(0.408065)	(0.294932)	(0.484042)	(0.425643)	(0.261946)	(0.29414)	(0.330463)	(0.42396)
Lag 1	1.6384	2.2204	0.8288	1.2188	0.8056	0.9472	1.0880	1.2134	0.9180	1.3743	0.9061	1.7847
	(0.3468)**	(0.586)***	(0.306818)	(0.277846)	(0.438377)	(0.250154)	(0.426051)	(0.375561)	(0.276714)	(0.476677)	(0.292463)	(0.60541)*
Event Week	0.7350	1.7537	1.1785	1.2125	1.6527	1.3135	1.1648	1.5913	0.7404	2.2951	1.4170	1.1121
	(0.1701)	(0.4333)**	(0.414853)	(0.260961)	(0.765665)	(0.302487)	(0.455275)	(0.494081)	(0.244122)	(0.7653)**	(0.451056)	(0.43679)
Lead 1	1.0389	1.3557	2.0410	0.8783	1.2259	2.3397	1.5165	1.0867	0.6734	1.2957	1.0553	1.0438
	(0.2385)	(0.3233)	(0.6669)**	(0.234896)	(0.674274)	(0.534)***	(0.58988)	(0.344496)	(0.235867)	(0.472508)	(0.361414)	(0.447056)
Lead 2	0.7978	0.9215	0.9876	0.8251	1.0777	0.9982	1.8117	1.6247	1.0047	1.5537	1.2817	0.6681
	(0.2251)	(0.2452)	(0.343831)	(0.231571)	(0.53977)	(0.274363)	(0.736503)	(0.513295)	(0.35296)	(0.556733)	(0.428662)	(0.296621)
Lead 3	0.8687	0.9955	1.3265	1.1002	1.0748	1.0470	1.1638	1.3389	1.0694	1.3776	0.9254	1.0740
	(0.2733)	(0.3986)	(0.400518)	(0.293681)	(0.485785)	(0.286138)	(0.488504)	(0.435518)	(0.418587)	(0.49457)	(0.318804)	(0.475994)
Lead 4	1.0083	0.8135	1.6633	0.7527	0.9554	1.1090	1.1393	1.5299	0.5979	1.4754	1.2908	0.6863
	(0.3531)	(0.4077)	(0.46562)*	(0.232372)	(0.444211)	(0.277007)	(0.494672)	(0.520344)	(0.281584)	(0.506666)	(0.412735)	(0.310398)
Lead 5	1.2455	0.8931	1.1147	1.2207	1.1889	0.9599	2.3502	2.0032	2.2731	1.3257	0.9385	0.4835
	(0.4405)	(0.4671)	(0.317336)	(0.363617)	(0.452422)	(0.234516)	(0.9961)**	(0.6789)**	(0.8496)**	(0.437082)	(0.30725)	(0.21242)*
Lead 6	1.7326	0.7049	1.2844	0.6928	1.0476	0.7471	2.1420	3.0862	2.0956	1.5627	0.8506	0.6404
	(0.6016)	(0.4137)	(0.332091)	(0.252027)	(0.390332)	(0.181993)	(0.9413)*	(1.021)***	(0.6839)**	(0.498559)	(0.274295)	(0.274519)
Lead 7	1.6830	0.9709	1.4232	0.7106	1.2909	0.5903	2.6174	2.3429	1.5972	1.2927	0.8224	1.1711
	(0.59)	(0.5789)	(0.335152)	(0.263741)	(0.484651)	(0.15941)*	(1.1783)**	(0.768)***	(0.483611)	(0.419799)	(0.269398)	(0.421701)
Posterior	1.3710	0.9809	0.6642	1.1336	1.6849	0.8117	1.5548	1.4452	1.3446	1.1146	0.8659	0.9632
	(0.2684)	(0.2037)	(0.1158)**	(0.163112)	(0.337)***	(0.122383)	(0.57247)	(0.341352)	(0.247536)	(0.252734)	(0.174529)	(0.211682)
Control	Infection Rate: 0.9984(0.0034), Vaccination Rate: 0.9517(0.0143)***, Emergency Dummy: 1.2691(0.0857)***,											
	Travel Subsidy Dummy: 0.6603(0.1542)*, Omicron Dummy: 1.3413(0.4816)											

Notes: The table reports coefficients of indicator of lecture style, following equation (5). Prior and Posterior mean endpoints of event window respectively. Lags represent weeks prior to lecture style changes. Event Week means at the week of lecture style change. Leads indicate weeks posterior to lecture style changes.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

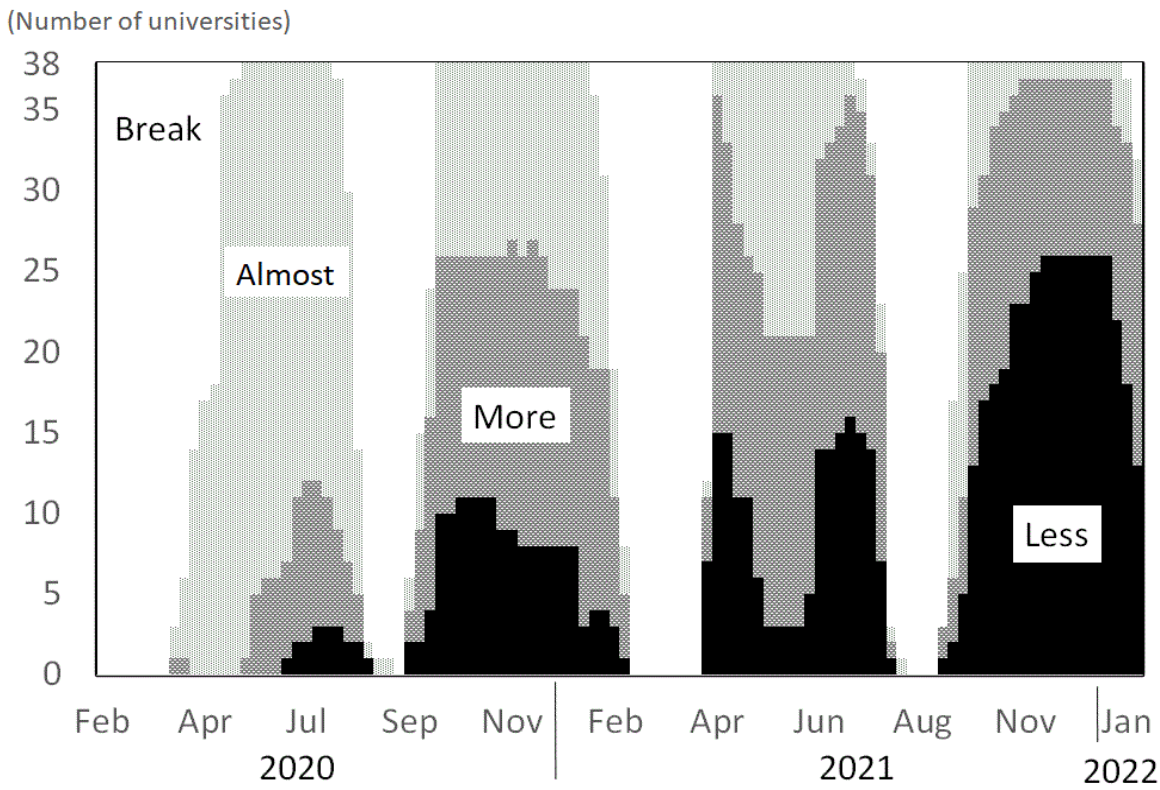
Figure 1: Weekly changes in new COVID-19 cases in Japan.



Notes: The black line depicts the weekly COVID-19 cases in Japan. The areas of darkly shaded and lightly shaded represent the periods under the state of emergency and under the pre-emergency measures in Tokyo, respectively.

Source: Japan Broadcasting Corporation

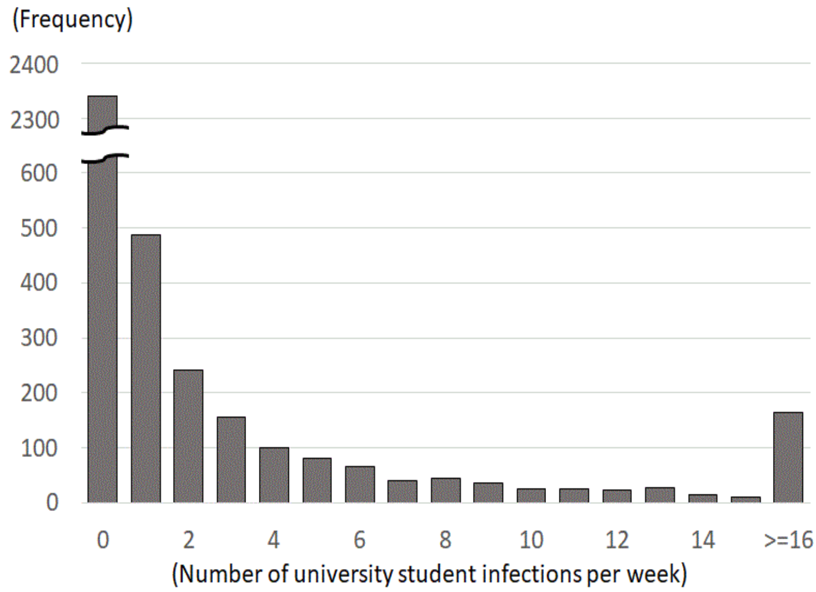
Figure 2: Lecture style changes during the study period.



Notes: "Breaks": long breaks. "Almost": lectures almost entirely or entirely online. "More": hybrid of face-to-face and online with half or more lectures online. "Less": hybrid of face-to-face and online with fewer than half of lectures online.

Source: Websites of each university

Figure 3: Distribution of university students' infections.

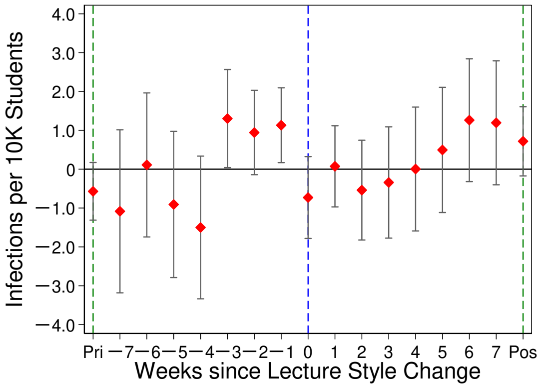


Notes: The horizontal axis shows the number of university student infections per week. The vertical axis represents the frequency of the number of infections per week. For example, the total number of weeks that reports 1 student's infection is 487. Because there were 38 universities and we conducted our analyses for 102 weeks, the total sample size was 3,876.

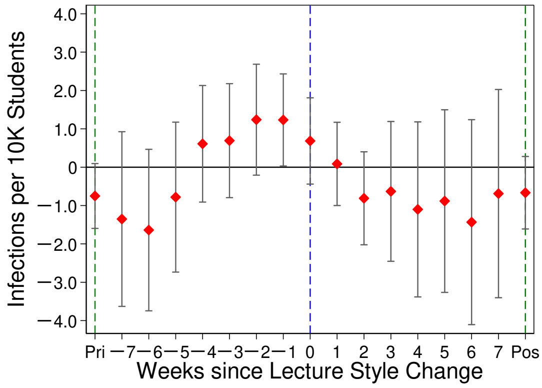
Source: Websites of each university

Figure 4: Baseline estimation results: during semesters.

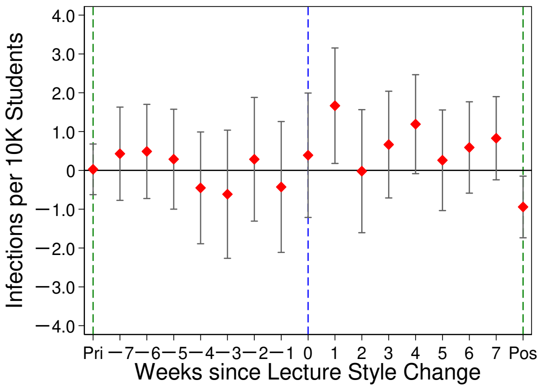
(a) Less to More



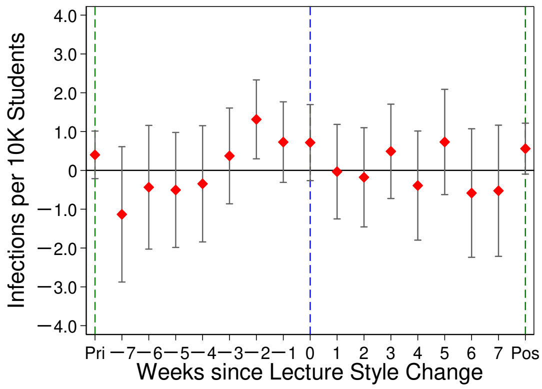
(b) Less to Almost



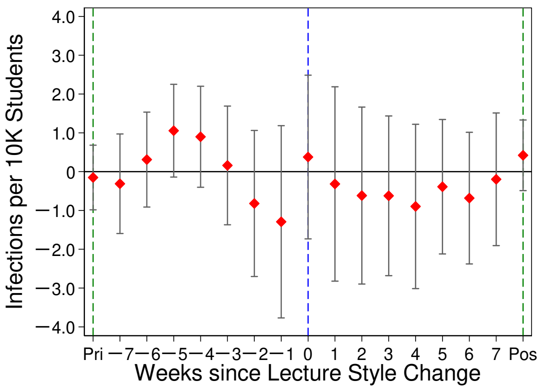
(c) More to Less



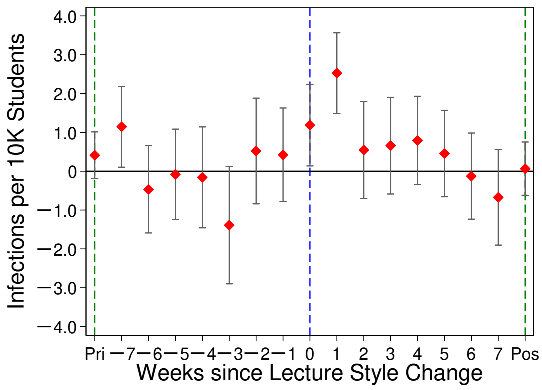
(d) More to Almost



(e) Almost to Less

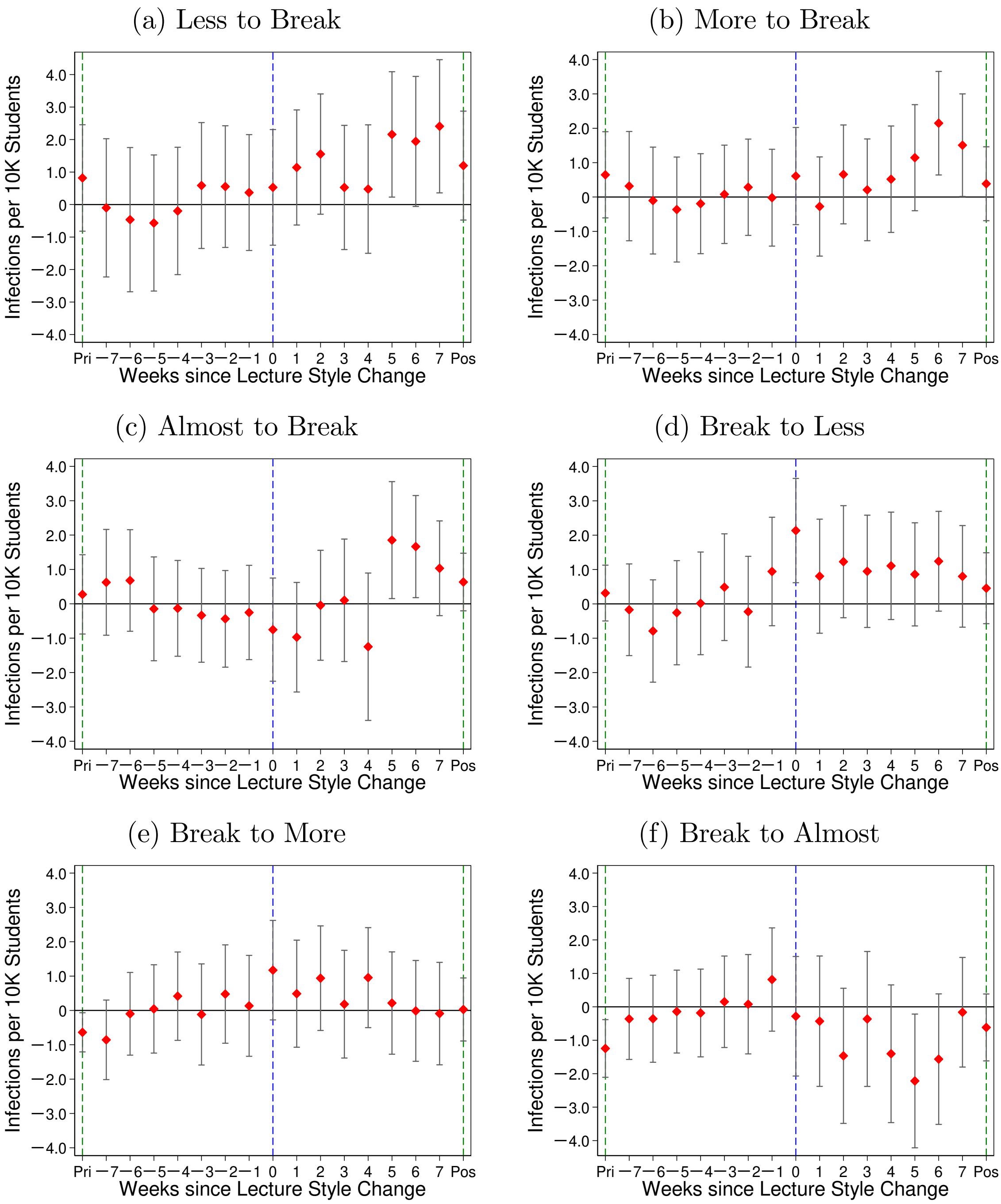


(f) Almost to More



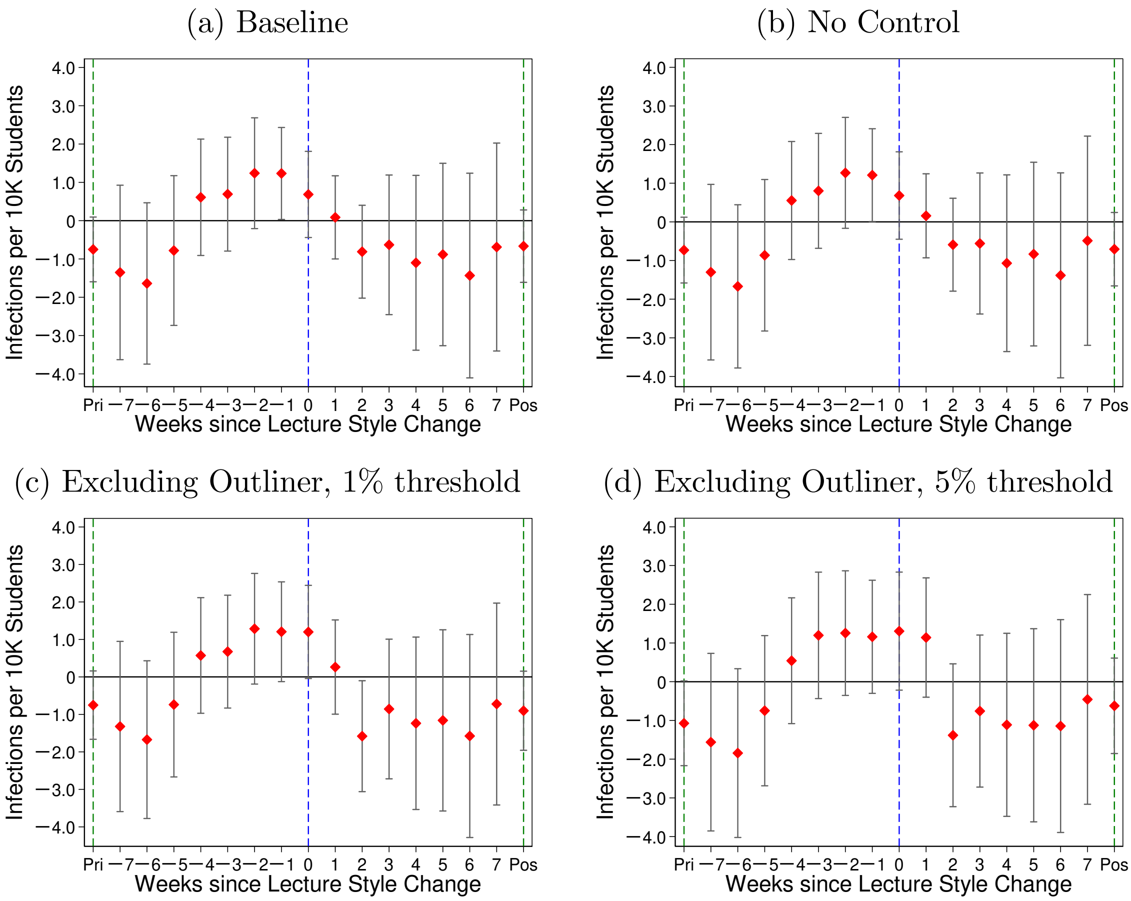
Notes: The vertical axis represents the deviations from the average infections per 10,000 students in a week. The mean number of infections between 7 weeks and 1 week prior to lecture style change is normalized to zero. The horizontal axis shows weeks prior and posterior to lecture style changes. Week 0 indicates the deviation at the week of changes. Red dots represent estimated means, and bars indicate 95% confidence intervals.

Figure 5: Baseline estimation results: breaks and semesters.



Notes: The vertical axis represents the deviations from the average infections per 10,000 students in a week. The mean number of infections between 7 weeks and 1 week prior to lecture style change is normalized to zero. The horizontal axis shows weeks prior and posterior to lecture style changes. Week 0 indicates the deviation at the week of changes. Red dots represent estimated means, and bars indicate 95% confidence intervals.

Figure 6: Robustness check: less than half online to almost entirely online.



Notes: The vertical axis represents the deviations from the average infections per 10,000 students in a week. The mean number of infections between 7 weeks and 1 week prior to lecture style change is normalized to zero. The horizontal axis shows weeks prior and posterior to lecture style changes. Week 0 indicates the deviation at the week of changes. Red dots represent estimated means, and bars indicate 95% confidence intervals.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- COVIDUniversityOkachiYounSupplemental.pdf