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Abstract

Universities are the only institutions that are still conducting most lectures through online during the prolonged COVID-19 pandemic. This study quantifies the effect of university lecture styles on the containment of spreading the novel coronavirus. Using the multiple event study model, we find that the cumulative increase in university students' infections from online only lecture style or long breaks to the combination of face-to-face and online lecture style is 5.2 per 10,000 students. Meanwhile, the opposite lecture style change reports the decline of 2.3 per 10,000 students. Other lecture style changes between almost online and these two lecture styles have relatively smaller effects. These results are robust to other models and omitting outliers.

Key words: COVID-19, University lecture style, Multiple event study model, Negative binomial distribution

JEL Classification: I18, I29

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1 Introduction

Since the outbreak of COVID-19 pandemic in Wuhan China in 2019, all people in the world have faced this serious crisis. Prior to the development of vaccines, we had few measurements to prevent the spread of this novel coronavirus (SARS-CoV-2). People wear masks or take physical distancing at an individual level, while many governments declare a state of emergency and regulate the flow of people at a society level. Figure 1 depicts the transition of the number of weekly infections in Japan and terms of the state of emergency in Tokyo. When the number of infections surged, the Japanese government announced the state of emergency four times to epicenters such as Tokyo and Osaka by September 2021. Schools from kindergartens to universities have also needed to take some measurements not to spread the coronavirus. For example, all public schools under the first state of emergency decided to delay the commencement of 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 measurements such as wearing masks and staggered attendance. Besides, the Japanese government had not requested for public K-12 to take strong measurements such as closing schools or taking only online lectures even at the time of from second to fourth state of emergency. However, many universities in Japan have been regulating face-to-face lectures since the outbreak of this pandemic in Japan at the beginning of 2020. 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 taking less than 50% of face-to-face lectures even not under the state of emergency. Many university students would be frustrated by not taking conventional face-to-face lectures for more than one and a half years. As an example of these frustrations, a student at Meisei university litigated his university on June 2021 to return a half of his tuition fees and compensate his or her mental distress. We believe it would be important to investigate whether university students' patience can lead to contain the spread of the coronavirus.

In this paper, we study the effects of university lecture styles on the number of infections among university students. The empirical strategy of our analysis is the panel event study model. According to Schmidheiny and Siegloch (2020), a growing number of papers are adopting the event study model. The term of "event study" was used in less than one percent of papers published by Top Five economics journals[1] in the 1990s, but the rate

[1]The Top Five economics journals are Econometrica, the Journal of Political Economy, the Quarterly

has been steadily increased, reaching about 4% in 2017. However, while most prior studies suppose a single event, we need to assume multiple events because universities frequently change their lecture styles. Askitas et al. (2021)[2] mention that [... multiple event study model is more challenging than in the single-event case], and only a limited number of papers adopt multiple event panel analysis (e.g. Schmidheiny and Siegloch, 2020; Ziedan et al., 2020). Thus, we carefully explain the treatment of multiple events in the section of model part. Moreover, many prior event study models assume the Gaussian distribution on the error term. However, the number of infections of each university would be regarded as a count data distributed close to zero. Thus, instead of the Gaussian distribution we assume the negative binomial distribution for the number of student infections, which is a dependent variable in our model. In order to confirm the validity of our estimation, we also analyze the case of a Poisson distribution as a robustness check. In addition to this, we exclude samples that exceed a certain threshold of infections per week as another robustness analysis. This is because most of these cases are considered as clusters that many students got infected at the same time by club activities.

The results of our analysis are as follow. We confirm that the university lecture style affects the number of student infections. For example, if universities change their lecture styles from online only or long breaks to the combination of online and face-to-face lecture style, the number of student infections is estimated to increase about 5.2 per 10,000 students in a total of 7 weeks prior and posterior to the change. Meanwhile, under the case of opposite lecture style change, the number of infections declines by about 2.3 per 10,000 students. This asymmetric effect is consistent with Glaeser et al. (2020) that relaxing regulations ease people's attitude toward the coronavirus and that lead to the spread of the coronavirus again. We also investigate the cases that universities change their lecture styles slightly. These results are consistent with our presumption that although we confirm the effects of lecture style change on the number of student infections, the effect is quite subtle. We check the validity of these baseline results by two robustness analyses of different models and omitting outliers.

The contributions of this paper can be summarized as follows. First, as far as we know,

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Journal of Economics, the American Economic Review and the Review of Economic Studies.

[2] They compare multiple policies to constrain COVID-19 infections such as international travel control, school closure, etc. Thus, several policies can be implemented at the same time, so the problem of multicollinearity may arise for their analysis. In order to avoid the problem, they apply the average value of intensity for each policy instead of the conventional dummy value of unity.

this is the first paper that examines the causal relationship between university lecture styles and university student infections. University education style under the COVID-19 pandemic is quite controversial. Meanwhile universities have been taking stricter measurements among all educational institutions, we do not know university student endurance is worth to contain the spread of coronavirus. This paper can provide the information to judge whether universities should regulate or moderate their lecture style. Second, instead of the conventional single event study model, we adopt a multiple event study model, that is getting popularity among economists these days. This model can be applied to the estimation of multiple event models because it is considered that not only university lecture styles but also many events can occur multiple times such as natural disasters or fiscal policies.

This paper is organized as follows. In Section 2, we present current literature of COVID-19, shedding light on behavioral restriction effects and event study models. In Section 3, we provide our model for the estimation. 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 strands of COVID-19 and event study model. First, there is a growing amount of literature that analyzes the relation of COVID-19 infections and measurements to contain the spread of coronavirus. Chaudhry et al. (2020) report that the effectiveness of lockdown varies among countries. Some Asian countries such as China, Taiwan and South Korea had achieved the reduction of more than 90% of new cases by adopting lockdown measurements, but Italy, Spain and the United States could not decline new cases as these Asian countries. Goolsbee and Syverson (2021) and Gupta et al. (2020) find limited impacts of local mobility restriction on the spread of the coronavirus. Besides, Glaeser et al. (2020) report that relaxing regulations can send a signal that moving around is no longer dangerous, and that can lead to an increase in infections again. Some literature sheds light on the effectiveness of school closure. Bravata et al. (2021) find that in-person visits to school increase the number of COVID-19 infections, although this magnitude is small. Courtemanche et al. (2021) report that reopening school increases the number of spreads gradually but substantially.

In terms of literature related to the methodology of the event study model, as Schmidheiny and Siegloch (2020) mention, it has been applied to many socioeconomic areas because of its straightforwardness of underlying econometrics and intuitive graphs. Bailey et al. (2019) study the relationship between parents' family planning and childhood economic resources. Dimitrovová et al. (2020) analyze the effect of primary care reform on the ambulatory care conditions. Venkataramani et al. (2020) investigate that closures of assembly plants led to high opioid overdose mortality rates. Suhonen and Karhunen (2019) report the spillover effect of high parents' accessibility to university on their child's attainment of years of education.

3 Model

We adopt an event study model for the analysis of the effect of university lecture style changes on COVID-19 cases of university students.[3] Although most of event study models assume that an event is one-shot (e.g. Simon, 2016; Fuest et al., 2018), we assume multiple event study analysis because universities change their lecture styles multiple times, including long breaks. Thus, following Ziedan et al. (2020), we formulate multiple-event study model as:

$$\log(\frac{Y_{u,t}}{U}) = \sum_{\pi} \sum_{j \geq \underline{j}}^{\overline{j}} \beta^{\pi,j} b_{u,t}^{\pi,j} + X'_{u,t}\Gamma + \mu_u + \theta_t + \varepsilon_{ut} \tag{1}$$

where

$$b_{u,t}^{\pi,j} = \begin{cases} \mathbf{1}[t = e_u^{\pi} + j] & \text{if } \underline{j} \leq j \leq \overline{j} \\ \mathbf{1}[t \geq e_u^{\pi} + j] & \text{if } j > \overline{j} \end{cases} . \tag{2}$$

In terms of the dependent variable $\log(\frac{Y_{u,t}}{U})$, $Y_{u,t}$ represents COVID-19 cases of each university, U is the number of university students. Subscripts u and t mean each university and time respectively. We normalize the number of university cases per their student number because infected people will increase in the larger size of universities. Then, we take natural logarithm on the dependent variable because the cases $Y_{u,t}$ is regarded as a count data and the variation of count data usually changes exponentially. Then, we can rewrite the equation

[3] These cases include not only university students but also staff and faculties. We will explain the detail of the count of COVID-19 cases in the next section.

(1) as:

$$\log Y_{u,t} = \sum_{\pi} \sum_{j \geq \underline{j}}^{\overline{j}} \beta^{\pi,j} b_{u,t}^{\pi,j} + X'_{u,t}\Gamma + \mu_u + \theta_t + \log U + \varepsilon_{ut} \tag{3}$$

The denominator of the dependent variable in equation (1) $\log U$ shifts to the right-hand side as an exposure variable. It is straightforward to assume that COVID-19 cases of each university $Y_{u,t}$ follow Poisson distribution or negative binomial distribution since $Y_{u,t}$ is a count data. However, it is considered that the negative binomial distribution would be flexible enough to estimate coefficients accurately because the Poisson distribution assumes identical values of mean and variance. In addition to this, the Poisson distribution is usually adopted when each event occurs independently. However, the occurrence of COVID-19 cases would be depending on past cases. Thus, we examine the validity of assuming the negative binomial distribution over the Poisson distribution with both Akaike information criteria (AIC) and Bayesian information criteria (BIC). These two criteria show the validity of the negative binomial distribution, so we confirm to adopt this distribution as a baseline estimation.[4] However, we also show the cases of Poisson distribution as robustness analyses.

Next, we explain the right-hand side of equation (3). The first term indicates changes of university lecture styles. $b_{u,t}^{\pi,j}$ represents binned event indicator expressed in equation (2), where π is lecture style changes and j shows time periods prior ($j < 0$) and posterior ($j > 0$) to the lecture style changes and at the week of lecture style change ($j = 0$). If j takes a negative (positive) value, the indicator represents lag (lead) of event occurrence. e_u^{π} indicates the week when a university u changes its lecture style as π. Lecture styles are categorized into three types; (1) online only or breaks, (2) almost online, and (3) the combination of face-to-face and online. Thus, there are six kinds of lecture style change. We explain the detailed classification of each lecture style in the next section. The event indicator $b_{u,t}^{\pi,j}$ takes unity j weeks after the lecture style change e_u^{π}, and zero otherwise. The interval of event time window is between $\underline{j}$ and $\overline{j}$, where $\underline{j}$ and $\overline{j}$ take negative and positive integers respectively. All future events posterior to the time window are taken into account as an indicator of long-term effect, meanwhile all past events prior to the time window are normalized to zero.[5]

[4] Chan et al. (2021) compare following four models for the analysis of COVID-19 infections: (1) Poisson and identity, (2) Poisson and log, (3) negative binomial and identity, and (4) negative binomial and log. They conclude that the case of (4) fits well for this analysis.

[5] The most common way to normalize the indicator is to set zero at the time of event (e.g. Clarke and Schythe, 2020; Schmidheiny and Siegloch, 2020). However, because we focus on the university students' infections around times of event occurrences, we normalize this indicator long before their occurrences

If an identical lecture style change is conducted more than one time, the value of long-term effect indicator $b_{u,t}^{\pi,\bar{j}}$ posterior to the time window is accumulated to be more than one. For example, if a university changes its lecture style from almost online to the combination of face-to-face and online twice, it takes the value of two for indicators $\bar{j}+1$ weeks after the second lecture style change. With respect to the length of event time window, it is usually assumed very long periods as Ziedan et al. (2020) point out. However, universities change their lecture styles frequently as is shown in Figure 3, so the coefficients of the indicator that are away from a timing of lecture style change might correspond to different lecture styles. Thus, it would be appropriate to take shorter periods on event time window than other conventional event study models. However, if we take too short period for event time window, we would not be able to estimate long time effect by lecture style change. Thus, we assume the interval of event time window as 7 weeks prior and posterior to the lecture style change, setting $\underline{j}$ and $\bar{j}$ to -7 and 7 respectively. Similarly, Ziedan et al. (2020) set 14 weeks as event time window, assuming lag indicator from -8 to -1 weeks and lead indicator from 0 to 6 weeks. Thus, they include the timing of event occurrence week as a lead indicator. However, we exclude the coefficient of indicator at the time of lecture style change from both lag and lead indicators because there exist some time lags between lecture style change and onset of coronavirus. According to Centers for Disease Control and Prevention (CDC), the incubation period of COVID-19 between exposure and the onset is estimated to be 4 or 5 days in the medium term. Therefore, the effect of lecture style change would not be apparent at the week of lecture style change, so we set the event time window as 15 weeks, taking the week of lecture style change as independent from lag and posterior indicators. The second term is university specific and time-varying controls, which consists of an infection rate, vaccination rate and mutation rate of each prefecture located to a university. The third term μ_u and fourth term θ_t are fixed effects of university and time respectively. The fifth term is the exposure that we have already explained. The last term ε_{ut} is the error term.

4 Data

First of all, we explain common characteristics of all data and our method to select universities for this study. We utilize following data for our analysis: COVID-19 cases and lecture

following some research such as Askitas et al. (2021). Even though we take different normalization times, interpretations of empirical results do not change at all.

style changes of each university, total infection rate, vaccination rate and rate of infection by the Delta variant. The frequency of data is weekly, and its range is from the third week of February (2/17 - 2/23) 2020 when all universities that we investigate were in spring vacation to the fifth week of July (7/26 - 8/1) 2021. We select forty Japanese universities as is shown in Table 1. The right column of each university name represents the number of their students. These universities are chosen from the category of national and public universities and private universities. In terms of the former universities, we collect 16 universities which disclose weekly or daily cases. We also collect data from the latter universities in order to increase the sample size. However, we restrict our investigation to private universities which have more than 8,000 students. This is because the university infection rate per student would be amplified if infection clusters happen in smaller size universities. In addition to this, we exclude some universities such as Ritsumeikan University because their campuses are scattered to several prefectures.[6] Among these universities, we finally collect 24 private universities which disclose weekly or daily cases.

Then, we will explain the detail of each data.

Number of infections of each university

It is varied among universities to disclose the content of COVID-19 infections. Thus, we standardize data of infection number as the following measurements. First, we include not only student infections but also academic faculties and staff because most of the universities do not disclose types of infected people in order to protect their privacy. Lecture styles, however, would also affect the infection number of university faculties and staff. Thus, it would be more comprehensive measurements to include their infections. However, we exclude the number of infected faculties and staff who work at their university hospitals if universities specify them because these infections are not related to lecture styles. Second, we do not distinguish places where students get infected. Although it would be considered that many student infections occurred outside of their campus, most of the universities do not disclose detailed information about it because of the difficulty to detect where and how

[6] Some universities also have branch campuses outside of the main prefecture such as Kyusyu university. However, if we exclude all these universities, the selection of universities would be biased with private universities, and most of the large size of private universities are located in large cities such as Tokyo or Osaka. This would not reflect the nationwide infection situation in Japan. Thus, in order to increase the sample size, especially national universities, we include universities which satisfies the following criteria: branch campuses are only for graduate students and the number of students is not so large in comparison with the student size in headquarter campuses.

they catch this coronavirus and also the problem of privacy. However, we think there is a correlation between university lecture style and off-campus infections because the face-to-face lecture style leads students to go outside with their friends after lectures. Thus, we regard it would be better not to distinguish places of students' infections because university lecture styles can also comprehend these off-campus infections. Third, we include several cases of the timing that universities recognize their student infections into cases of the timing that students recognize their infections. This is because some universities do not inform the timing of student infections but provide the timing when universities get the information about their student infections. It is considered that there are lags of several days between two timings. However, because we collect a weekly dataset, many cases of two timings will be contained in the same week. Besides, even though some samples are counted to the next week, it would not have a significant impact on statistical results to measure whether university lecture styles affect the number of student infections or not. Fourth, there are some cases that universities disclose the number of infections with a duration of several days rather than specific days. In this case, we calculate average infections per day and add to weekly infections. For example, if a university discloses 12 student infections in 3 days and the first two days are a different week of the last day, 8 student infections are counted in the former week.

Figure 2 shows the frequency of the number of infections per week. No infection was reported in more than a half of total samples, and the number of frequency declines as more students got infected in a week. Thus, it is straightforward to assume that the distribution of this data follows the negative binomial or Poisson rather than Gaussian.

Lecture style

As we have explained in the previous section, the lecture style is categorized into (1) online only or breaks, (2) almost online, and (3) the combination of face-to-face and online. However, universities have been setting their own criteria about the degree of online and face-to-face lectures. Thus, we need to categorize their lecture styles. If universities are in long breaks or adopt online only, we regard this style as (1) online only or breaks. Breaks are regarded as the same category with online only lecture style since students do not take face-to-face lecture style in these periods.[7] If they allow face-to-face style for some lectures

[7] The duration of winter break, which is from the end of December to the beginning of January, is about one week. Thus, we exclude this break to categorize into type (1) online only or breaks. The number of infections during this period would be captured by the time fixed effect.

such as experiments or practical exercises, we judge this style as (2) almost online. Other lecture styles are categorized into (3) the combination of face-to-face and online. The typical example of type (3) lecture style is that universities allow face-to-face style for smaller size lectures under the adequate measurement not to spread the coronavirus although more than half lectures are conducted through online. [8] We exclude the style of normal face-to-face lecture because there was no university that took this lecture style during our analysis between February 2020 and July 2021.[9] Next,

Figure 3 shows the transition of university lecture style. When the Japanese new school year had started in April 2020, few universities took almost online style. The majority of universities postponed to start new semester or started lectures with only online. As the number of infections in Japan declined in around June or July, many universities attempted to take face-to-face lecture style partially. After the summer break, the number of infections had been suppressed to be low and scientists began to understand the virus's low infectivity to younger people. Thus, all universities allowed face-to-face lecture style at least partially, and about half of the universities took the style of the combination of face-to-face and online. However, as the infection situation deteriorated from around the end of 2020, universities began to restrict face-to-face lecture style. The infection situation has improved during the spring vacation, so many universities started a new school year with combination lecture style in April 2021. However, the infection situation deteriorated again during the 1st semester and the majority of them took almost online lecture style around May. Although the situation had improved in a short period after June, the number of infections had increased again and the government declared the state of emergency in July. The severe situation continued until the end of this semester and about 40 % of universities took almost online or online only.

Control Variables

We adopt three control variables: infection rate, vaccination rate and variant rate. These three variables are calculated from each raw number of each prefecture divided by its pop-

[8] Along with the lecture style, a university's policy on extracurricular activities can also be considered as a factor that has an important influence on the number of infected people on campus. However, since the policy on extracurricular activities is closely linked to the policy on lecture style, the policy on lecture style can be considered to reflect the policy on extracurricular activities.

[9] Japanese universities start the Spring break in January or February until April of the commencement of the new school year. In April 2020, the first wave of COVID-19 hit Japan and the Japanese government declared the state of emergency in several major cities including Tokyo and Osaka. Since then, national and larger size of private universities which we analyze have not returned to the normal lecture style.

ulation.[10] The population data was taken from the statistics bureau of Japan. Following is the explanation of each raw number. First, we extract the number of COVID-19 infections by prefecture from Japan Broadcasting Corporation. This is daily data, so we convert it to weekly data. Next, in terms of the number of vaccinated people, we get the data of the number of people vaccinated twice. Although healthcare workers got vaccinated earlier than other people, the vaccination for other people had started from the first week of May 2021. This data was obtained from the government chief information officers' portal, Japan. Finally, many types of variants have been founded and spread all over the world since the first COVID-19 was discovered in Wuhan China. The original type or other early variants were recognized weak infectivity for younger people, so the infection rate of younger people had been lower than older people. However, since the more powerful Delta variant began to spread in Japan around May 2021, the infection rate among younger people had increased. Thus, we include the Delta variant infection rate as a control variable. This data is taken from Ministry of Health, Labour and Welfare.

5 Result

Figure 4 shows the dynamic graphical result of our main estimates. "Only" stands for online only or breaks, "Combo" means the combination of online and face-to-face lecture style, and "Almost" represents almost online lecture style. For example, the first figure "(a) Only to Combo" describes the transition of student infection number prior and posterior to the lecture style change from online only or breaks to the combination of online and face-to-face. The zero week represents at the time of lecture style change. The dependent variable of the estimated equation (3) is taken natural logarithm, so we take exponential for the coefficients. Besides, we standardize these coefficients taken exponential as the deviation from the average infections of a week per 10,000 students of all sampled universities in order to grasp figures intuitively. Red dots represent estimated mean values and bars indicate 95 percent confidence intervals.

As we have explained, Figure (a) shows the effect of lecture style change from online only

[10] In terms of the infection rate, although there exists city level infection data, we adopt prefecture level data. This is because it is better to use data that is consistent with other prefecture level data of vaccination rate and variant rate. In addition to this, many students are also living outside of cities located their universities. Prefecture level data is more comprehensive as a control variable in this case.

or breaks to the combination of online and face-to-face. The number of infections clearly increases after universities relax their restrictions on face-to-face lectures. The cumulative infection difference between 7 weeks prior and posterior to the lecture style change is about 5.2 per 10,000 students. Because the total number of university students in Japan was about 297.3 million in 2019[11], so it is roughly estimated that the total number of university student infections will increase by 1,542 in 7 weeks due to this lecture style change.

Figure (b) reports the lecture style change from "Only to Almost". The infection number prior to the lecture style change is lower than that at the time of the change. The infection situation is relatively stable after the lecture style change. The cumulative difference between prior and posterior lecture style change is about 2.0 per 10,000 students. From this and the previous figure, we observe that the number of infections under the lecture style of online only or long breaks has been lower than the average infections.

Figure (c) provides the result of "Almost to Only". It is expected that the number of infections declines by this lecture style change, but it is increasing until the next week of the change. This would reflect the scientific evidence that the incubation period of COVID-19 is 4-5 days in the medium term and up to 14 days (Centers for Disease Central and Prevention, CDC). The number begins to decline two weeks after the change and falls below the average in three weeks.

Figure (d) exhibits the case of "Almost to Combo". The number of infections is stable two weeks prior to the lecture style change, but the number increases one week before the change. This would be considered as announcement effect. Universities announce their future relaxation of regulations before their implementation. That would be regarded as a message to students to be allowed to take riskier behaviors. The number of infections has been higher than the average for about one month after the change.

Figure (e) displays the transition from "Combo to Only". The infection situation deteriorates only at the time of lecture style change. The cause of this deterioration is that some universities coincidentally disclose their university student infections at the commencement timing of their university breaks. As Figure 3 shows, the change of this lecture style is the least among all lecture style changes. Thus, the coefficient of this indicator is more likely to capture this coincidental case. To reflect this argument, this infection increase is not persistent but temporary, and the situation improves soon after universities restrict face-to-face

[11] This data was taken from statistics bureau of Japan. We subtract colleges of technology (so called kōsen) because they include the period of high school.

lectures. Next, the notable point is the asymmetric effect of lecture style change. The figure shows that changing to online only or breaks from the combination style has a limited effect on the reduction of the number of infections (-2.3 per 10,000 students in 7 weeks), compared to the increase by relaxing the regulation of face-to-face lectures as Figure (a) shows (+5.2 per 10,000 students in 7 weeks). This result is consistent with Glaeser el al. (2020) that if regulators moderate mobility restrictions, people regard the situation as safer and tend to be more careless. This suggests that regulators need to recognize this asymmetric impact of restrictions and moderations.

Figure (f) shows the case of "Combo to Almost", which also exhibits announcement effect. Universities announce to regulate face-to-face lectures when the infection situations deteriorate several weeks before their lecture style changes. Then, the number of infected students had begun to decline prior to their implementation. This is considered that faculty members regulate face-to-face lectures more at their discretions, and students abstain from their riskier behaviors.

As a reference, Table 2 shows our estimation results, displaying mainly the coefficients of indicator of lecture style. The coefficient values do not necessarily show statistical significance. This is partly because students get infected not only in classrooms but also in other places such as club activities or by their family members. Thus, even though we control infection situations of each prefecture located to the universities, it is impossible to extract pure effects of lecture style change. The other reason would be several lags between infection, confirmation and disclosure. It is varied among students to inform their symptoms to their universities after they get infected. Also, some universities do not disclose the confirmation date of student infections but the timing that universities recognize their infections. These lags would also affect the results of statistical significance. Thus, some results show wider ranges of 95% confidence interval. However, although some coefficients of indicator do not report statistical significance, it is possible to grasp the overall tendency of whether university infections are spreading or abating and these approximate magnitude of infections. In order to confirm the validity of these results, we examine robustness checks with two methods. We explain these methods and results in the next section. We also list the long-term effect by lecture style changes. As we explained before, the effect posterior to 8 weeks are taken into account as this coefficient. All coefficients are consistent with our conjecture that the regulating face-to-face lecture style declines the number of infections and relaxing the style leads to the high number of infections. The biggest degree of change is from the combination to online only or breaks by the decline in 0.75 point, which corresponds to 0.6 per 10,000 students in the normalized scale per week. In other words, this lecture style change can have the long-term effect to decrease the standard of infections by 0.6 per 10,000 students. The degree of change of other coefficients is lower than this lecture style change.

To sum up, it can be regarded that the university lecture style generally affects student infection. As we expected, the number of student infections increases if universities take more accommodative styles of face-to-face lectures, and vice versa. When universities change their lecture style greatly such as from online only to the combination, the effect of the change on the number of infections is apparent. However, if they change their lecture styles mildly, the number of infections is a subtle difference between prior and posterior to the lecture style change. In addition to this, we observe the asymmetric effect of lecture style change. That is the number of infection changes is larger when universities deregulate the face-to-face lecture style than they restrict this style.

6 Robustness

We conduct two robustness analyses to examine the validity of the main results. The first robustness check is analyses under different control variables and distribution of the dependent variable. We include all control variables and assume a negative binomial distribution for the dependent variable under the baseline estimation, but we examine five alternative models as is depicted in Table 3. The first column (a) shows the baseline case. The second column (b) examines the model without any control variables under a negative binomial distribution. The third column (c) provides the case with only a control variable of infection rate under a negative binomial distribution. We examine only this case as the inclusion of the control variable because the infection rate indicates statistical significance as Table 2 shows. The following columns (d), (e) and (f) exhibit cases of Poisson distribution for the dependent variable under the identical control variables corresponding to (a), (b) and (c) respectively.

Figure 5 shows the only robustness result of the lecture style change from online only or breaks to almost online in order to avoid the redundancy of explaining other robustness results. The reason why we select this combination is that this is the most frequent combinations among other lecture style changes. The effects of other changes are explained in the online appendix. Figures (b) and (c) report similar results to the baseline model. While the cumulative difference between 7 weeks prior and posterior to the lecture style change in the baseline model is 2.0 per 10,000 students, this difference of figures (b) and (c) are 2.3 and 1.9 per 10,000 students respectively. Meanwhile, figures under the assumption of Poisson distribution (d), (e) and (f) report a slightly higher level of spreading coronavirus after the lecture style change to almost online. As a result, the cumulative differences between prior and posterior to the lecture style change in figures (d), (e) and (f) are 4.9, 6.1 and 4.8 respectively. Cases of other lecture style changes under the Poisson distribution also report higher fluctuation than the cases of negative binomial distribution.

We also examine a robustness analysis of omitting outliers since several cases of university student infections can be regarded as clusters that occur outside of classes such as club or circle activities. We use the method to find the outliner introduced by Davies and Gather (1993) under the assumption that the number of infections follows the negative binomial distribution defined as:

$$f(x;k,m) = \frac{\Gamma(k+x)}{\Gamma(k)x!}\left(\frac{k}{k+m}\right)^k\left(\frac{m}{k+m}\right)^x$$

where k and m are parameters satisfying $\mathbb{E}(x) = m$ and $Var(x) = m + \frac{m^2}{k}$. We estimate that the values of m and k are 1.37 and 0.23 respectively. Then, we derive the threshold of omitting value as 8 per 10,000 students with the conventional significance level of 0.05. The threshold will be shifted in proportion to the number of students of each university. For example, the threshold for Meiji university is 22 infections in a week since the university has 33,310 students, while that value for Fukushima university, which has 4491 students, is 3 infections. The total number of omitting samples is 134, which would be regarded as a relatively large number. Thus, we also examine the cases of a significant level of 0.01. The threshold of the number of infections is 16 people and the number of omitting samples is 20. Figure 6 shows results of the mean estimation of baseline, 0.01 significant level and 0.05 significant level. Three estimations report a similar result. We anticipated that results of omitting samples would estimate a lower effect of university lecture style change. However, outliners would have already been captured by both university and time fixed effects of the baseline results.

Therefore, we confirm the validity of the result of baseline estimation from these two robustness analyses.

7 Conclusion and Discussion

In this paper, we examine the effect of university lecture change on the spread of COVID-19 in university students. The methodology of estimation is the panel multiple event study model with an assumption of negative binomial distribution for the number of university student infections.

Our analysis shows apparent effects of university lecture style change on their infections. If universities change their lecture styles from online only or long breaks to the combination of online and face-to-face lecture style, the infections will increase about 5.2 per 10,000 students in the accumulation of 7 weeks prior and posterior to the change. Meanwhile, the opposite lecture style change has an asymmetric effect on the infection that the degree of infection number decline is small, reporting 2.3 per 10,000 students. If universities change their lecture styles from almost online to these two lecture styles, their effects on the students' infection are mild, so as the changes of opposite lecture styles. These results are confirmed with two robustness analyses.

There are several limitations of our analysis. First, the model does not specify the duration of university lecture styles after a university changes it. There were several cases that university lecture styles have changed again within the event time window, but we treat lecture style changes uniformly. This study is not for the comparison of the infection effect of taking a particular lecture style in the short term or long term but for quantification of the effect of lecture style change on the number of infections. However, we might be able to provide additional empirical results if we distinguish the duration of lecture styles. Second, the result of our analysis weighs on the original type of coronavirus, that is regarded as weak infectivity to young people. However, several variants with stronger infectivity have been replacing the original type. In Japan, the infection rate of younger generation has been substantially low until March 2021. However, the alpha variant, which was first discovered in the U.K., hit Japan from April 2021, and the Delta variant, which was first discovered in India, increased the number of Japanese infections including younger generations. We might underestimate the number of university student infections under the case of Delta variants.

Last but not least, we would make comments for university administrators. This paper does not recommend them to relax or restrict the degree of face-to-face lectures but merely provides results of empirical analysis. However, our analysis reports that the number of university student infections will not increase so much by the slight expansion of face-to-face lectures. Besides, it has passed more than one and a half years for university students not to go to their universities adequately. Recent papers find the correlation between the quarantine or self-isolation and the deterioration of children and adolescents' mental health (Liu et al., 2020, Tang et al., 2021). Although the constraint of spreading coronavirus might be the top priority for universities, there may be still some measurements that universities can do for their students such as starting face-to-face lectures for small size classes. We hope universities stand for the perspective of students and provide the best lectures during this difficult times.

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Tables and Figures

Table 1: Universities

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	Takushoku Univ.	9,676		
Mie Univ.	7,252	Nanzan Univ.	9,672		
Fukushima Univ.	4,491	Konan Univ.	9,256		

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

Source: Toyokeizai, retrieved from <https://toyokeizai.net/articles/-/190960?page=3>

Table 2: Baseline Estimate

Indicator	(a) Only to Combo	(b) Only to Almost	(c) Almost to Only	(d) Almost to Combo	(f) Combo to Only	(f) Combo to Almost
Lag 7	-0.1734	0.0901	0.4687	-0.1271	-0.1579	-0.3281
	(0.3122)	(0.3216)	(0.2207)**	(0.2416)	(0.3003)	(0.3329)
Lag 6	0.0459	-0.1237	0.0290	-0.1423	0.0120	-0.3870
	(0.3432)	(0.3513)	(0.2390)	(0.2454)	(0.2877)	(0.3078)
Lag 5	-0.4520	-0.0914	-0.7082	0.1190	-0.0872	0.0526
	(0.3668)	(0.3630)	(0.2687)***	(0.2417)	(0.2984)	(0.2606)
Lag 4	-0.4972	-0.6873	-0.1593	0.2593	-0.1224	-0.2078
	(0.3339)	(0.4073)*	(0.2206)	(0.2578)	(0.2893)	(0.2752)
Lag 3	-0.6112	-1.0915	-0.2332	-0.0910	-0.3177	0.4151
	(0.3265)*	(0.4137)***	(0.2402)	(0.3139)	(0.3217)	(0.2024)**
Lag 2	-0.8471	-0.3845	0.0331	0.2146	0.1490	0.6846
	(0.3014)***	(0.3373)	(0.2480)	(0.3517)	(0.3252)	(0.1872)***
Lag 1	-0.5059	-0.0725	0.0932	0.8538	0.0717	0.5316
	(0.2798)*	(0.3312)	(0.2480)	(0.3036)***	(0.3670)	(0.1824)***
Event Week	-0.1549	0.0042	0.1717	0.3210	1.0387	0.3732
	(0.2587)	(0.3252)	(0.2588)	(0.3342)	(0.3498)***	(0.1824)***
Lead 1	-0.2906	-0.0715	0.3463	0.4760	0.0608	0.0403
	(0.2551)	(0.3312)	(0.2560)	(0.3353)	(0.4570)	(0.2180)
Lead 2	0.0707	0.0283	0.2539	0.3709	-0.5879	-0.5164
	(0.2452)	(0.3152)	(0.2897)	(0.3015)	(0.7607)	(0.2534)**
Lead 3	0.0584	-0.1742	-0.2649	0.3208	-0.5740	-0.0038
	(0.2561)	(0.3236)	(0.3542)	(0.2754)	(0.6247)	(0.2252)
Lead 4	0.3389	0.0772	-0.7065	0.5852	-0.5639	-0.5556
	(0.2500)	(0.2955)	(0.4032)*	(0.2646)**	(0.5144)	(0.3059)*
Lead 5	0.4857	0.0564	-0.2979	-0.4441	-1.2774	-0.1434
	(0.2467)**	(0.2922)	(0.3283)	(0.3847)	(0.5061)**	(0.2910)
Lead 6	0.7176	-0.0115	0.0319	-0.8007	-0.2696	-0.5273
	(0.2434)***	(0.2844)	(0.2748)	(0.7482)	(0.3719)	(0.3504)
Lead 7	0.4955	0.2460	-0.4522	-0.7967	-0.4077	-0.1876
	(0.2546)**	(0.2709)	(0.2829)	(1.0459)	(0.3568)	(0.3418)
LTE	0.4416	0.1787	-0.4312	0.2959	-0.7528	-0.2190
	(0.1931)**	(0.2048)	(0.1986)**	(0.2178)	(0.2273)***	(0.1635)

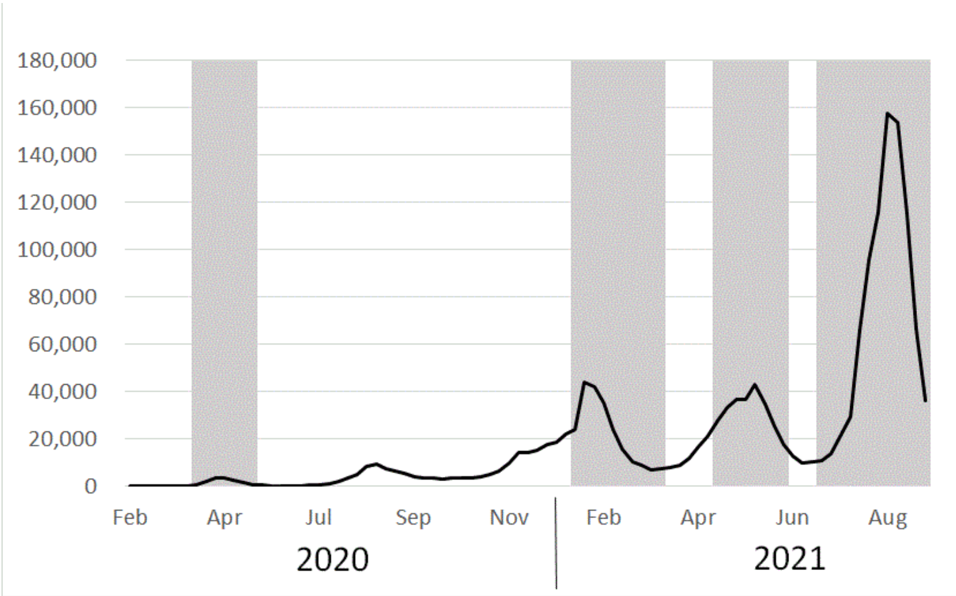
Notes: The table reports coefficients of indicator of lecture style, following equation (3). Lags represent weeks prior to lecture style changes. Event Week means at the week of lecture style change. Leads indicate weeks posterior to lecture style changes. LTE shows long-term effect. Clustered standard errors are in parentheses. Coefficients and standard errors of other control variables are as follows: prefecture control is 0.1451(0.0228)***, vaccination control is -0.0376(0.0453) and delta variant control is 2.6198(4.9557). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Models for Robustness Checks

	(a)	(b)	(c)	(d)	(e)	(f)
NB / Po	NB	NB	NB	Po	Po	Po
Infection rate controls	Yes	No	Yes	Yes	No	Yes
Vaccination controls	Yes	No	No	Yes	No	No
Delta variant controls	Yes	No	No	Yes	No	No

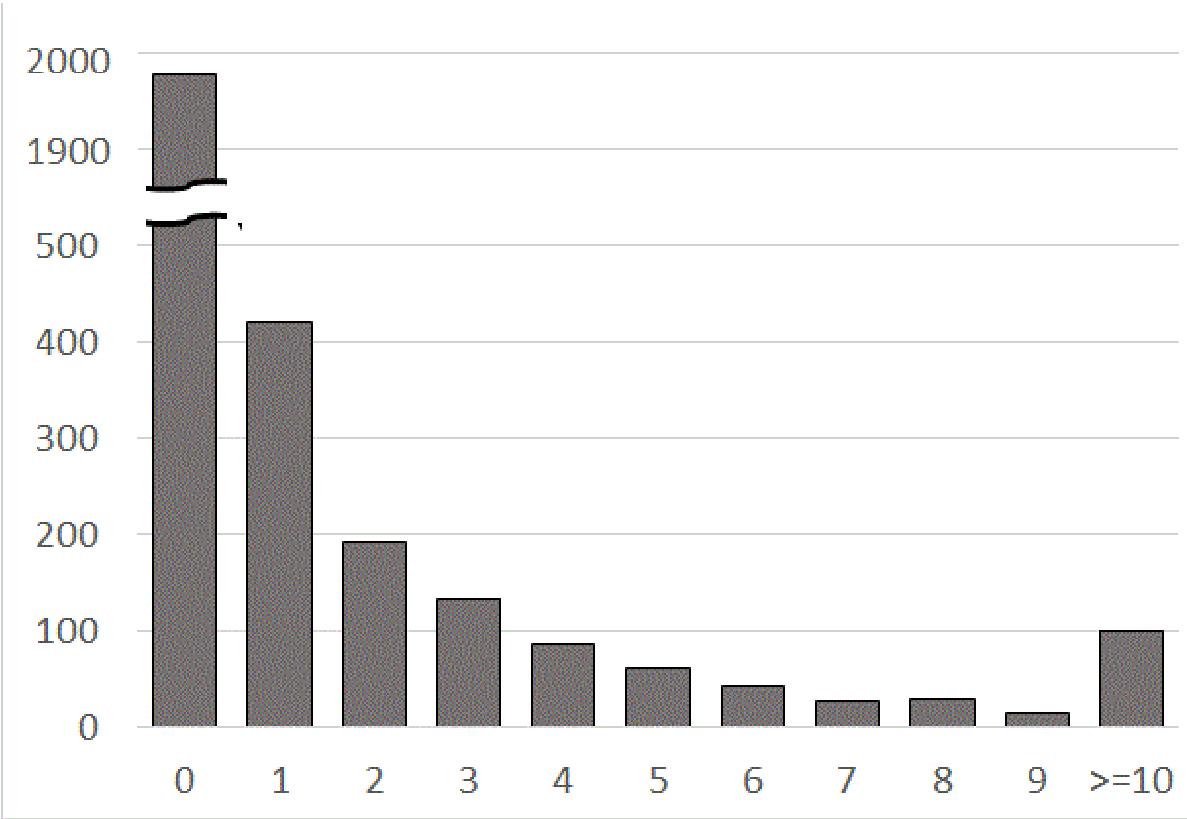
Notes : (a) is used for the estimation of the baseline model. (b) and (c) assume the negative binomial distributions for the dependent variable. The former model sets no control variable and the latter model controls only the infection rate. Other models (d), (e) and (f) assume the Poisson distribution for the dependent variable, corresponding to identical controls for model (a), (b) and (c) respectively.

Figure 1: Weekly Transition of New COVID-19 cases in Japan



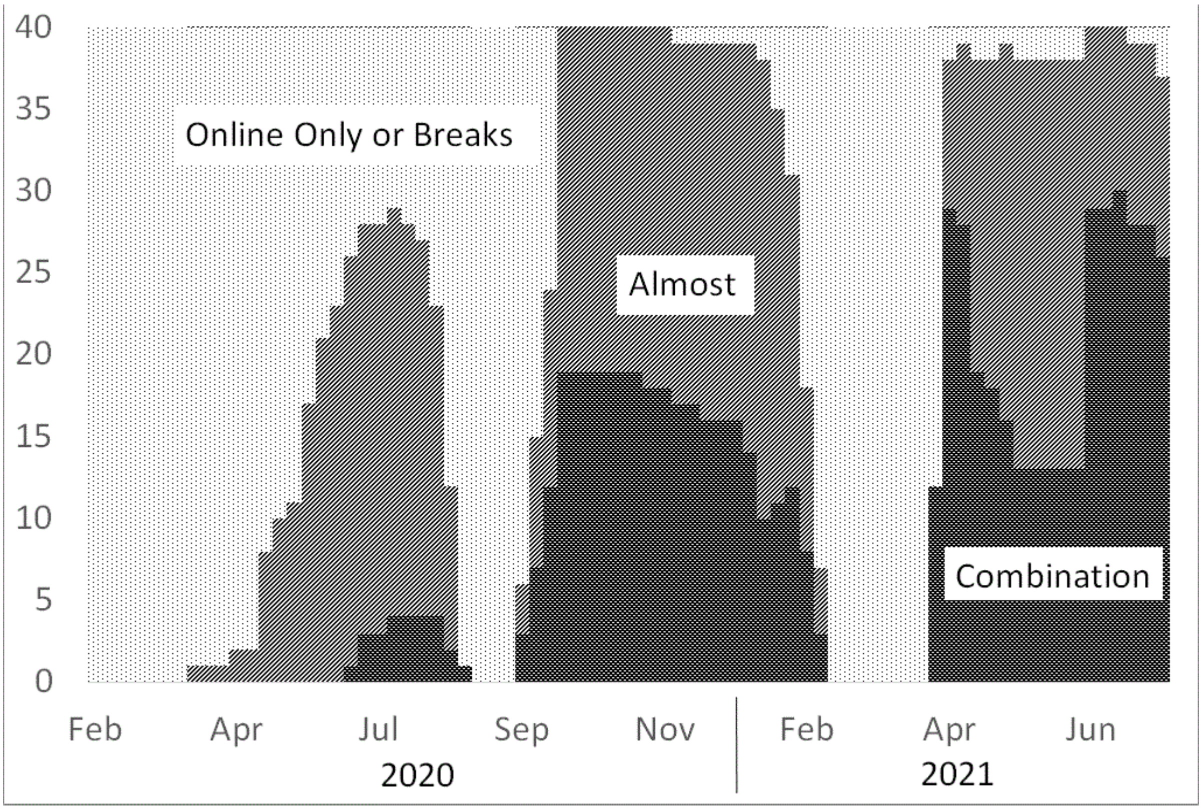
Notes : The black line depicts the weekly COVID-19 cases in Japan. The shaded areas represent the time under the state of emergency in Tokyo.
Source: Japan Broadcasting Corporation, retrieved from
<https://www3.nhk.or.jp/news/special/coronavirus/data/>

Figure 2: Distribution of University Students' Infections



Notes : The horizontal axis shows the number of university student infections per week. The vertical axis represents the total number of occurrences of per week infections. The number of university is 40 and the length of our analyses is 76 weeks, so the total sample size is 3040.
Source: Websites of each university

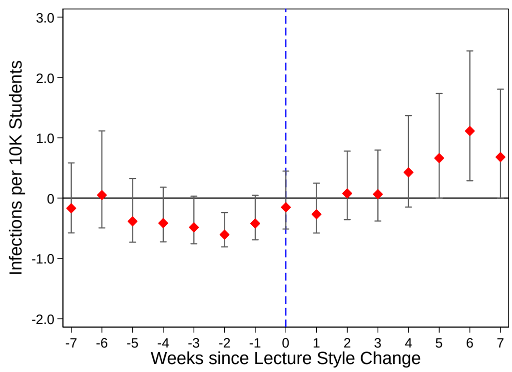
Figure 3: Lecture Style



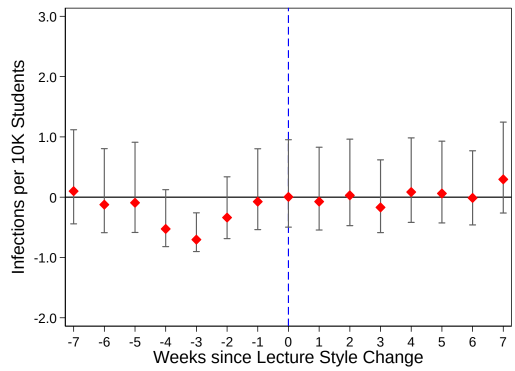
Notes : "Online only and breaks" means online only lecture or in long breaks. "Almost" represents almost online lecture style."Combination" shows the combination of face-to-face and online lecture styles. The vertical axis indicates the number of universities.
Source: Websites of each university

Figure 4: Result of Baseline Estimation

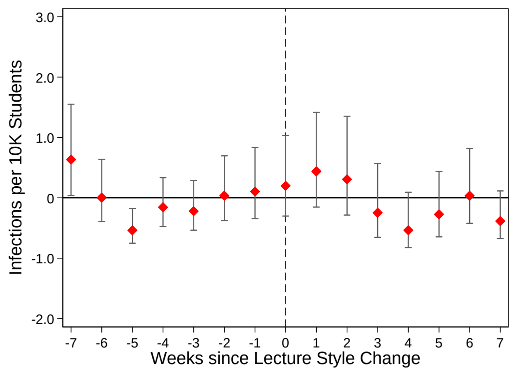
(a) Only to Combo



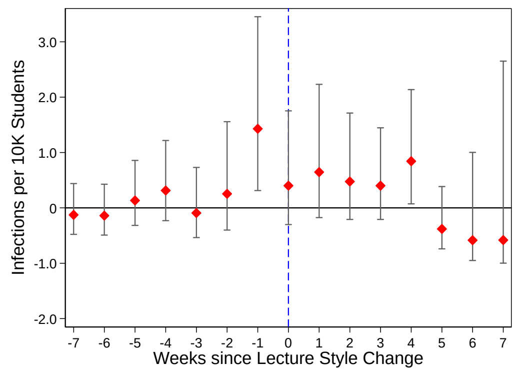
(b) Only to Almost



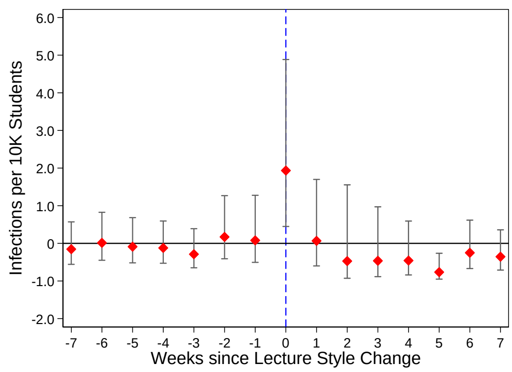
(c) Almost to Only



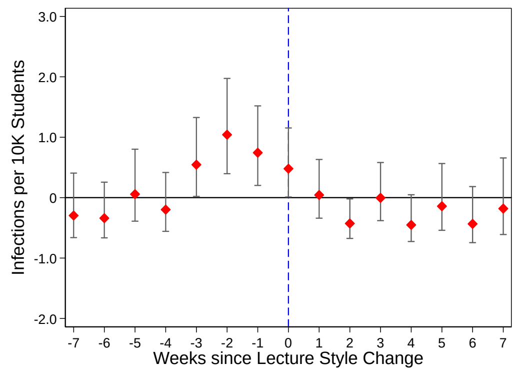
(d) Almost to Combo



(e) Combo to Only

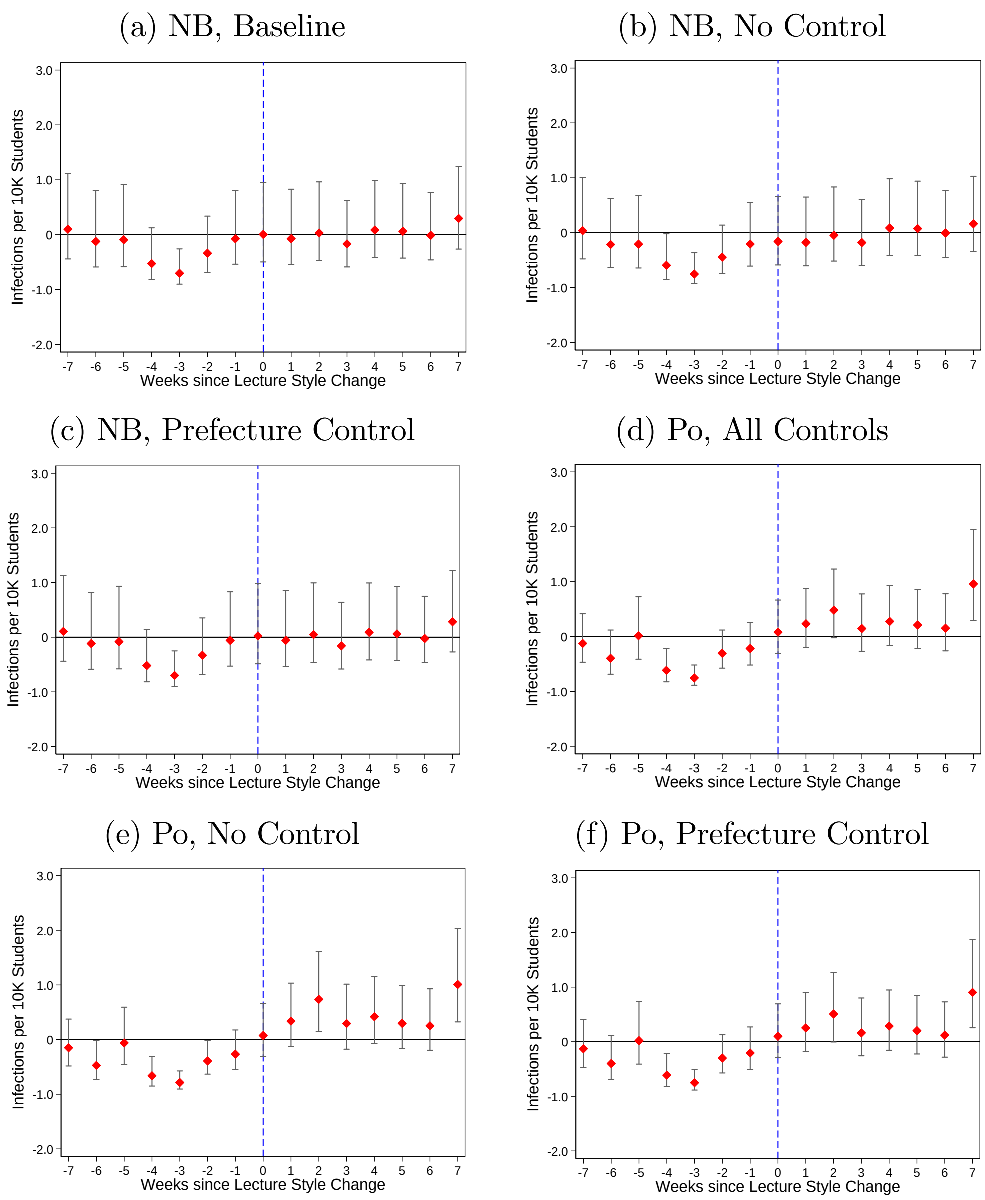


(f) Combo to Almost



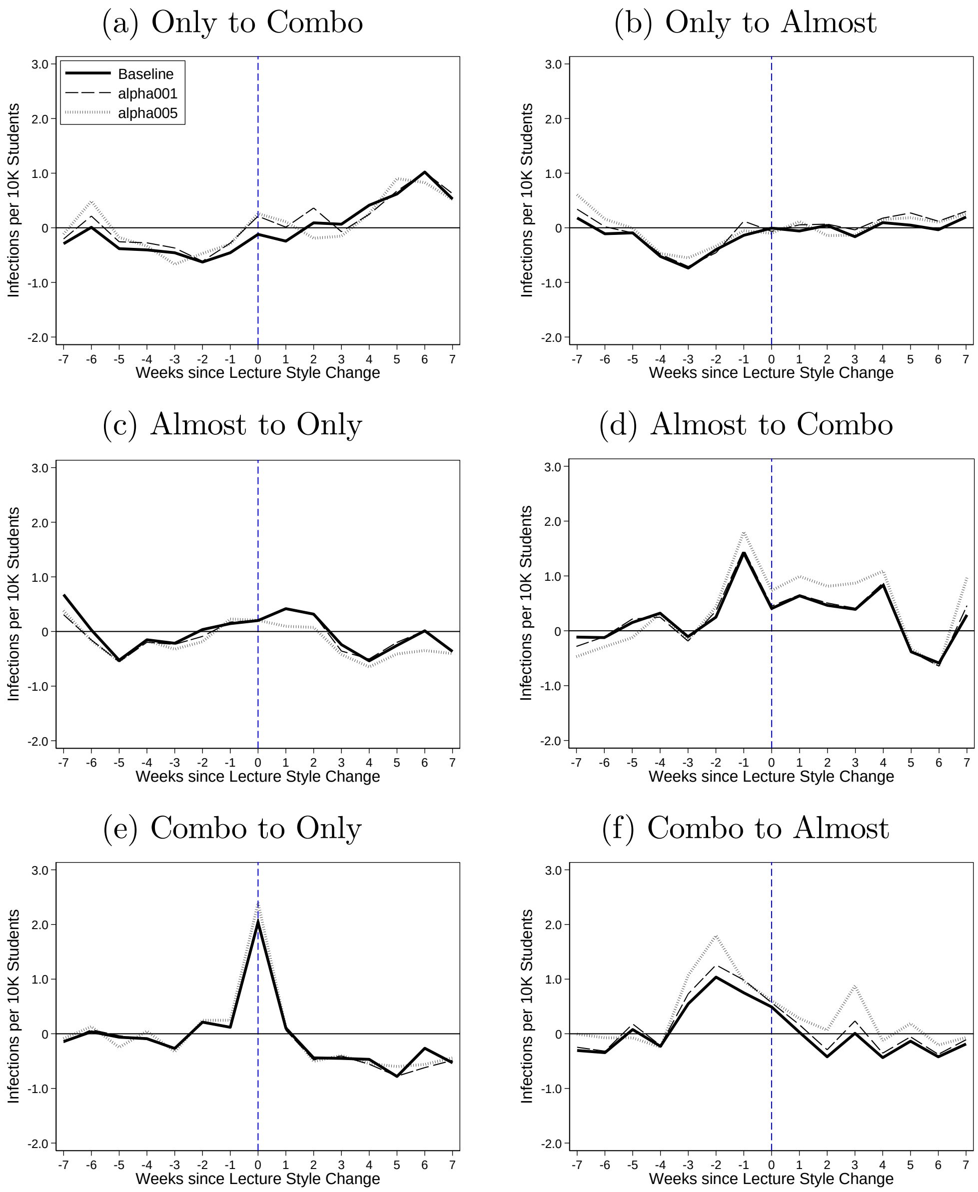
Notes: The vertical axis represents the deviations from the average infections per 10,000 students in a week. The horizontal axis shows weeks prior and posterior to lecture style changes. Week 0 indicates the deviation at the week of changes. Red dots represent estimated mean values and bars indicate 95 percent confidence intervals.

Figure 5: Robustness Check by Various Models (Online Only or Breaks to Almost Online)



Notes: All figures show the lecture style change from online only or breaks to almost online under various models. "NB" and "Po" stand for negative binomial and Poisson distributions respectively. Table 3 explains the detail of each model.

Figure 6: Robustness Check by Omitting Outliers



Notes: alpha001 and alpha005 represent the point estimation results by omitting outliner samples with 0.01 and 0.05 significant levels respectively.