Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

JUE Insight: College student travel contributed to local COVID-19 spread☆

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ABSTRACT

Due to the suspension of in-person classes in response to the COVID-19 pandemic, students at universities with earlier spring breaks traveled and returned to campus while those with later spring breaks largely did not. We use variation in academic calendars to study how travel affected the evolution of COVID-19 cases and mortality. Estimates imply that counties with more early spring break students had a higher growth rate of cases than counties with fewer early spring break students. The increase in case growth rates peaked two weeks after spring break. Effects are larger for universities with students more likely to travel through airports, to New York City, and to popular Florida destinations. Consistent with secondary spread to more vulnerable populations, we find a delayed increase in mortality growth rates. Lastly, we present evidence that viral infection transmission due to college student travel also occurred prior to the COVID-19 pandemic.

1. Introduction

"If I get corona, I get corona. At the end of the day, I'm not gonna let it stop me from partying." – University student interviewed by CBS News on March 18, 2020

Thousands of college students flocked to spring break destinations in March 2020, garnering international media attention and arousing concern that increased travel with population dense social interactions could increase COVID-19 spread (BBC News, 2020; CBS, 2020; CNN, 2020; Montgomery and Fernandez, 2020; VOA, 2020). Given the age-mortality gradient of COVID-19 (CDC, 2020; Zhou et al., 2020), young Americans face a greater divergence in social costs and internal costs than older age groups. President Trump addressed this externality in a White House Press Briefing saying, "They're feeling invincible... but they don't realize that they can be carrying lots of bad things home to grandmother and grandfather and even their parents" (WhiteHouse.Gov, 2020). Given the high social cost of an infection (Bethune and Korinek, 2020), quantifying the impact of college student travel on local COVID-19 growth is a question of first-order importance.

University policies aimed at reducing infections should target spread within the university *and* account for the externalities imposed on the surrounding community.

We study how travel by U.S. college students affects the spread of viral infections both during and prior to the COVID-19 pandemic. We collect spring break dates for 1326 universities which enroll a total of 7.5 million students.[1] In doing so, we create a sample of universities with break dates between the end of February and end of April. We argue and provide evidence that the timing of a university spring break is uncorrelated with factors related to the potential spread of COVID-19. Due to the rapid suspension of in-person classes, we separate universities that did and did not have spring break as scheduled prior to the pandemic.[2] We pair smartphone location data with the timing of university spring breaks to show stark differences in mobility for universities with early versus late spring breaks. To compare the evolution of COVID-19 case and mortality growth rates in counties that have universities with early spring breaks to counties with universities with late spring breaks, we use a difference-in-differences research design. As we show using smartphone location data, counties with early spring breaks

exhibit remarkable student outflows during spring break and *then similar inflows after spring break*. On the other hand, late spring break students left campus upon the suspension of in-person classes and largely did not return.

Our findings suggest that university students returning from spring break contributed to the growth rate of COVID-19 cases in the county of the university. The increase in case growth rates begins the week after the early spring break university students returned to campus, denoting an increase in primary infection of traveling students. The increase peaks two weeks after students returned, which suggests secondary spread. Although the difference in the growth rate of cases was temporary, by April 30th, early spring break counties had 20% higher confirmed cases per capita than late spring break counties.[3] We find no evidence of an immediate increase in COVID-19 mortality growth rates, which is expected given the low mortality-risk to college students. However, we provide evidence that growth in confirmed mortality may have increased three to five weeks after early spring break students returned to campus, denoting an increase in mortality due to secondary spread to higher-risk individuals. Using smartphone location data, we trace where students traveled for spring break and by mode of transit. We find that early spring break universities with students who were more likely to transit via air, to New York City, and to Florida contribute more to COVID-19 spread than early spring break universities with less of this travel. On the other hand, we do not find evidence that universities with more students traveling via cruiseliners differentially contributed to local infection spread.

We also show that college student travel contributed to viral infection spread *prior to the COVID-19 pandemic*. Using data from the Google COVID-19 Search Trends Symptoms Dataset, we estimate the effect of university spring break timing on search intensity for common symptoms of viral infections. We find that, in the weeks after students return from spring break, search intensity for illness symptoms increases in counties with a higher population share of college students relative to neighboring counties with no universities and counties with fewer college students. Therefore, even after the pandemic subsides, college student travel may continue to spread viral infections.

For the remainder of the COVID-19 pandemic and beyond, universities have several policy levers that can shift the behavior of college students in order to reduce the risk of infection spread both on campus and to the surrounding community.[4] First, universities hosting students on campus can adjust academic calendars to alter or remove breaks during the semester that allow students to travel and return to campus. This adjustment has the potential to reduce spikes in infections both on campus and at the students' travel destination, but may come at the cost of harming the mental health of both students and faculty. Next, universities can limit parties and gatherings of large groups, reduce density in dormitories, and require facial coverings which are shown to reduce the spread of infections (Karaivanov et al., 2020; Lyu and Wehby, 2020; Bahl, Eikmeier, Fraser, Junge, Keesing, Nakahata, Wang). Universities can also choose to cancel sports during the remainder of the pandemic. Although this decision comes at a much greater financial cost to universities, these interactions, whether during tailgating, waiting in line, or inside the stadium, allow for potentially infected college students to spread infections to members of the surrounding community.[5] Lastly, at

the conclusion of the semester or if universities again shift classes online and close campuses, administrators should take precautionary measures before sending potentially infected students home to prevent spreading infections to more vulnerable populations outside of the university community.

2. Background

The risk of COVID-19 spread in the United States quickly escalated at the end of February 2020, just as many university students were preparing for spring break. On February 26th, roughly the beginning of university spring break season, the first case of community spread in the United States was reported. On February 29th, the first confirmed COVID-19 death in the United States was reported (NPR, 2020). On March 1st, United States Secretary of Health and Human Services, Alex Azar, stated, "...the risk to average Americans remains low. We are working to keep it low". It was not until March 11th, three days after many students would return from break, that the World Health Organization declared COVID-19 a pandemic and the United States announced it would suspend travel from most of Europe. It is within this context that university students made decisions regarding spring break travel.

While the effects of university policies on COVID-19 spread have thus far gone understudied, the effects of state and local Non-Pharmaceutical Interventions (NPIs) on COVID-19 outcomes have received much attention (Andersen, 2020; Courtemanche et al., 2020; Dave et al., 2020a,b; Friedson et al., 2020; Flaxman, Mishra, Gandy, Unwin, Coupland, Mellan, Zhu, Berah, Eaton, Perez Guzman, et al.). These studies typically analyze the dynamic effect of Shelter-in-Place Orders (SIPOs), restaurant and entertainment closures, large gathering bans, and school closings on COVID-19 outcomes. Courtemanche et al., 2020, for example, find that SIPOs and restaurant and entertainment closures reduce COVID-19 cases, but find no such evidence for public school closures. Abouk and Heydari (2020) also find that SIPOs were effective in reducing mobility and decreasing COVID-19 cases and similarly report that K-12 school closures had no beneficial impact on reducing mobility. These results suggest that K-12 schools were not a significant secondary spreader of infections prior to closure.

In contrast, we expect university campuses to pose a greater threat to community spread than K-12 schools. First, on-campus residency results in a more dense living arrangement for college students which would increase the potential spread within a university. Second, evidence suggests that university students interact with a larger number of other students. For example, at Cornell University, the average student shares a classroom with 529 other unique students each semester (Weeden and Cornwell, 2020). Lastly, as discussed in Bursztyn et al. (2020), Allcott et al. (2020), Simonov et al. (2020), Painter and Qiu, 2020, willingness to social distance has been a function of political stance, news viewership, and mortality-risk. Considering college students face relatively low mortality-risk coupled with a higher degree of agency than K-12 students, this demographic may be less likely to abide by social distancing guidelines. Alfaro et al. (2020) claim that fear reduces individual mobility and "stringency measures matter less if individuals are more patient and altruistic preference traits." Given that young college students might have less fear and higher discount rates, we expect college students to have higher mobility than the general population during the COVID-19 pandemic.

Large jumps in mobility due to spring break are particularly concerning, as Fang et al. (2020) highlight the importance of mobility restrictions in China on reducing the spread of COVID-19. Additional evidence from the 1918 Flu Pandemic suggests that reducing mobility and discouraging formations of large groups is instrumental in "flattening the curve" (Barro, 2020). Goscé et al. (2014) propose that the infection rate

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[3] Figure A.3 plots cumulative cases and mortality per 1000 county population by early versus late spring break counties.

[4] Andersen et al. (2020) document the role that college re-openings played in propagating COVID-19. They find that in the first few weeks of the Fall 2020 semester, universities that chose to host students on campus contributed to an additional 3000 COVID-19 cases per day nationwide.

[5] The directional flow from lower-mortality risk university students to higher-mortality risk community members is especially relevant given work that finds large spectator sporting events can propagate viral spread and increase influenza mortality (Stoecker et al., 2016; Cardazzi et al., 2020). Additionally, Ahammer et al. (2020) find that one additional NHL or NBA game in March 2020 led to a 9% increase in COVID-19 deaths in the local county. While it is possible to play college sports without fans in attendance,

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Lindo et al. (2018) find a 15% increase in the reporting of sexual assault near college campuses on the day of away games, suggesting that college party culture surrounding football games does not require stadium attendance.

of a disease is a highly nonlinear function of crowd density, suggesting that dense formations of students at spring break destinations may have high infection rates.[6] Kraemer et al. (2020) find that travel restrictions may be especially effective in the beginning stages of growth, implying that enhanced travel for spring break between February 28th and March 8th may have contributed to the initial spread of COVID-19.

Previous research shows that universities and college students exert both positive and negative externalities on surrounding communities. Universities have a positive economic effect on surrounding areas via increasing private research and development, tax revenue, and spreading human capital (Jaffe, 1989; Anselin et al., 1997; Siegfried et al., 2007; Woodward et al., 2006; Andersson et al., 2009; Abel and Deitz, 2012; Kantor and Whalley, 2014). However, the negative externalities that universities impose on the surrounding community have only more recently been studied. Some of these studies outline the negative externalities of youth alcohol consumption (Carpenter, 2005; Fertig and Watson, 2009; Carpenter and Dobkin, 2015; 2011), while others show that partying associated with college football games increases sexual assaults in the local areas surrounding games (Lindo et al., 2018). We contribute to this literature by documenting another potential externality that universities may impose on the surrounding region: increased spread of viral infections due to college students.

Like Harris (2020) and Cotti et al. (2020), we are interested in studying contributing factors to COVID-19 growth. While travel by itself can contribute to increased infections, the mode and destination of student travel can further increase the risk of infections. Kuchler et al. (2020) use Facebook social network data and find a positive relationship between social connectedness of a county to Westchester County, New York and COVID-19 cases, suggesting that travel to and from hotspots can contribute to COVID-19 spread. In addition to studying the effect of college student travel on COVID-19 spread, we also investigate whether travel to particularly risky destinations might have a larger impact on local contagion.

3. Data

3.1. University data

We collect spring break dates for 1326 universities in the United States.[7] While dates for some universities were obtained from Statravel.com, we collected over 1000 spring break dates from academic calendars hosted on university websites. These four-year public and non-profit institutions enroll over 7.5 million students.[8] We also include university student body characteristics from the Integrated Postsecondary Education Data System (IPEDS) and from the College Scorecard to compare universities with early and late spring break dates.

3.2. COVID-19 confirmed cases and mortality

We use county-day level confirmed COVID-19 case and mortality data from the New York Times (NYT, 2020) accessed on May 3, 2020. We caution that these are *confirmed* cases, as confirmed cases are an imperfect estimate of true cases. This issue is highlighted by work showing that positive test rates in New York City vary across demographics and income levels (Borjas, 2020; Schmitt-Grohé et al., 2020). However, nei-

ther county-level positive test rates nor the total number of tests are available for the dates of our sample.[9]

3.3. Mobility data

We use SafeGraph Social Distancing Metrics to measure the mobility of college students. This data uses GPS pings derived from the smartphone application usage of "trusted third-party data partners". SafeGraph provides aggregated device counts at the Census Block Group (CBG) level. In order to identify which devices are likely to be college students, we collect the CBG associated with each university in our sample. SafeGraph defines devices within a 153×153 m square as "home", where "home" is calculated using the primary location of the device at night over a six week period. Therefore, for the majority of traditional university students, home will either be a university dormitory or off-campus housing. We are most interested in tracking whether, on a given day, students are traveling. Specifically, we use counts of devices that are pinged more than 50 km from "home" in a given day.[10] The dataset also includes counts of device flows from "home" CBGs to destination CBGs. Using this, we count the number of devices which traveled to popular Florida spring break destinations, New York City, airports, or cruise ports.

3.4. Airport data, cruise port data, and county demographics

We assign airports and cruise ships to CBGs using geospatial data from the Federal Aviation Administration and cruise ports from the U.S. Department of Homeland Security. We estimate the percent of devices, by university, that visited an airport or cruise port over spring break.[11] We also use county-level demographics and characteristics from Killeen et al. (2020) and county-level temperature data from the National Oceanic and Atmospheric Administration (NOAA) to compare observables across early versus late spring break counties.

4. Empirical strategy

We use a difference-in-differences research design to estimate the causal effect of university student travel on COVID-19 spread in the local county by leveraging plausibly exogenous variation in the timing of university spring breaks. Since universities designed academic calendars years in advance of the COVID-19 pandemic, our treatment dates are not impacted by the reverse causality concerns relevant to research studying the impact of state and local NPIs on COVID-19 outcomes (Goodman-Bacon and Marcus, 2020). In order to interpret our difference-in-differences estimates as causal, it should be the case that potential COVID-19 spread in late spring break counties would be similar to that of early spring break counties had university students in early spring break counties not returned to campuses after their travel. Although our difference-in-differences estimates rely on the parallel trends assumption and not random assignment, if counties with early or late spring breaks are otherwise similar on key observables such as population, demographics, and density, COVID-19 contagion might also evolve similarly across these sets of counties in the absence of treatment.

To support this claim, we test whether universities and counties with early spring breaks differ in key observables. Universities are defined as having an early spring break if the break was scheduled to end prior to

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[6] Evidence in Dave et al. (2020c) suggests one such "super spreader" event was the Sturgis Motorcycle Rally in Sturgis, South Dakota which attracted nearly half a million people and lead to large increases in infection spread in the home counties of the participants.

[7] From the universe of four-year degree granting institutions from IPEDS, we remove all for-profit universities and universities which have more than 50% of their undergraduate population online. We drop any university with missing enrollment and student characteristics data from IPEDS. We drop any university with special focus status, all U.S. service academies, and any university which has predominately graduate enrollment.

[8] Enrollment numbers come from the 2018 Integrated Postsecondary Education Data System (IPEDS).

[9] We believe differential access to testing should not be a large concern since treatment status is defined by academic calendars published years in advance. We also present evidence that treatment status is balanced along dimensions such as income and physicians per capita.

[10] The SafeGraph data reports counts of devices binned by travel thresholds. The threshold for 50 km or more is the maximum of this binning which counts devices traveling the furthest from "home."

[11] We are able to cleanly identify travel to highly trafficked airports because large airports are typically assigned their own CBG (United States Census Bureau, 2020).
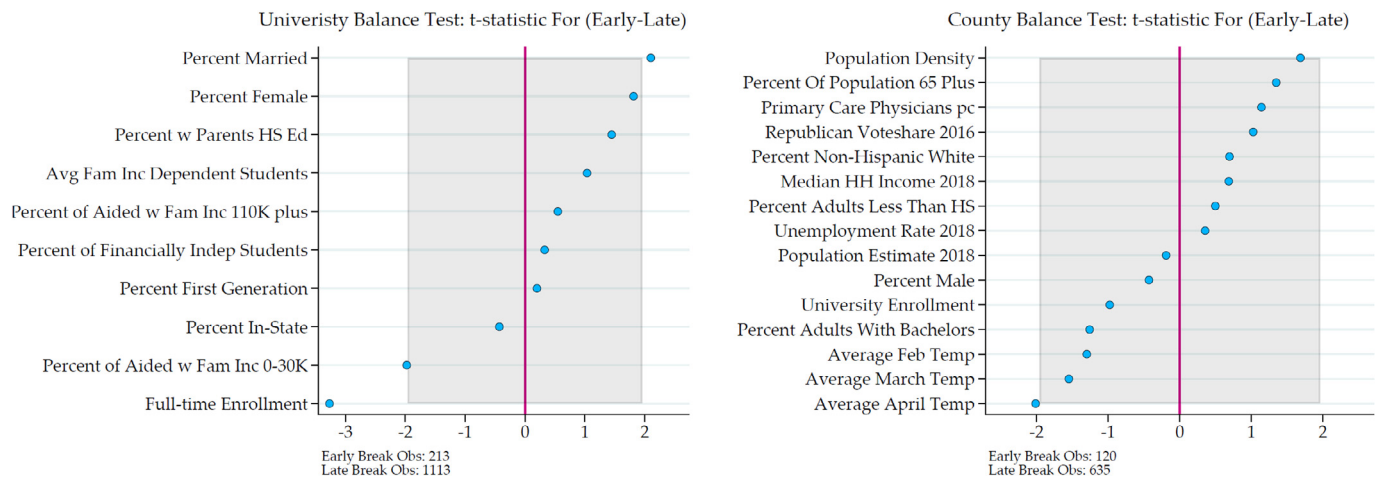
Fig. 1. Difference in Means Test Statistics by Early and Late Spring Break for Universities and Counties. Notes: The figures above plot the test statistics from tests for a difference in means between early and late spring break universities (left) and counties (right). A full table of means, standard deviations, mean differences and test statistics can be found in Table A.1. Universities are assigned as early spring break if the university spring break ended prior to March 9th (213 out of 1326 universities). Counties are assigned as early spring break if at least 25% of the college student enrollment in the county had a spring break ending prior to March 9th (120 our of 755 counties). The shaded region represents the critical value for the 95% confidence interval. All data for universities come from IPEDS or the College Scorecard. Data for counties come from Killeen et al. (2020), MIT Election Lab, and NOAA.

March 9th.[12] The sample contains 213 early spring break universities and 1113 late spring break universities.[13] Since many counties have multiple universities and COVID-19 outcomes are observed at the county level, we define a county as having an early spring break if at least 25% of the county's college student population had an early spring break.[14]

Fig. 1 plots the test statistics for a test of difference in means between early and late units. Universities with early or late spring breaks are largely similar in the composition of the student body.[15] The university-level balance table shows that early spring break universities tend to have lower enrollments and have larger shares of female and married students. Additionally, universities with early spring breaks have fewer aided students with family income less than $30,000. At the county level, treatment is largely balanced along median household income, primary care physicians per capita, population, and other variables. Early spring break counties tend to have colder February-April temperatures.[16] Additionally, early spring break counties had slightly higher (but not statistically different) Republican vote share during the 2016 election which has been shown to be correlated with a reluctance to engage in social distancing (Painter and Qiu, 2020). One cause for concern is that the population density of early break counties is greater than that of late break counties.[17] However, this population density imbalance is driven by only three outlier early spring break counties. In Appendix A.2, we show that our results are robust to removing these high density early spring break counties.

Despite their similarities in observables, students who attended early spring break universities had the opportunity to continue with scheduled spring break plans while students at late spring break universities largely did not return to campus after their scheduled spring breaks. We use SafeGraph mobility data for devices residing on university campuses to show how college student travel over spring break differed for early and late spring break universities. Panel A of Fig. 2 shows the share of university-residing devices that traveled more than 50 km from the university over the period between February 15th and March 30th for the group of early spring break universities. During their scheduled spring breaks, university-residing devices were between 20 to 40 percentage points more likely to have traveled over 50 km from the university. Additionally, when spring break ended, these devices returned to the university at the same rate. However, between March 12th and March 20th, as universities suspended in-person classes and instructed students to leave campus, these devices again leave the university area but do not return to campus.[18]

On the other hand, Panel B of Fig. 2 shows the travel behavior of students with later spring breaks separately by which week the spring break was originally scheduled. All four sets of universities show remarkably similar behavior until March 6th. On March 6th, the universities scheduled to begin spring break are indeed more likely to travel away from campus for vacation. However, these devices do not return to campus at the conclusion of spring break due to the suspension of in-person classes. Additionally, beginning on March 12th, university residing devices with later spring breaks begin to leave the campus area as universities suspend in-person classes. The suspension of in-person classes results in a large outflow of university students with a negligible share of university-residing devices returning to campus. As a result, the universities with early spring breaks had students leave the campus area for regularly scheduled spring break travel and *subsequently return to campus after their travel.* However, later spring break university-residing devices

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[12] Prior to March 9th, only 9 universities had suspended in-person classes, and university students with these spring breaks largely traveled without much concern for COVID-19. However, over 80% of universities had suspended in-person classes by March 15th (Marsicano et al., 2020).

[13] 15 ending on March 1st and 198 ending on March 8th for the early period. 475 ending on March 15th, 377 ending on March 22nd, 178 ending on March 29th, 34 ending on April 5th, and 49 ending after April 5th. Figure A.2 shows a histogram of the university spring break dates along with a timeline of the closure of universities.

[14] We show robustness to various thresholds of this measure in Figure A.1.

[15] Full balance tables with means and mean differences are provided in Table A.1.

[16] While some studies have shown higher temperatures are associated with more COVID-19 infections (Xie and Zhu, 2020), others have shown no effect of average, minimum, or maximum daily temperatures on infection spread (Briz-Redón and Serrano-Aroca, 2020). These contradictory findings may be due to weather being an important determinate for social distancing behavior (Wilson, 2020). To alleviate this concern, we estimate an alternative specification in Appendix A.2 where we include state-by-week fixed effects to reduce the variation in temperatures across comparison groups.

[17] Bisin and Moro (2020) note that differences in population density across cities can have dramatic effects on the evolution of contagion even when the cities have the same population. Denser cities not only reach peak infections sooner, but also have higher peaks of active infections which may strain a city's medical capacity.

[18] Marsicano et al. (2020) provides detailed information regarding the suspension of in-person classes and the transition to remote learning for universities across the United States.

A. Share of devices more than 50km from home (Early Spring Breaks)
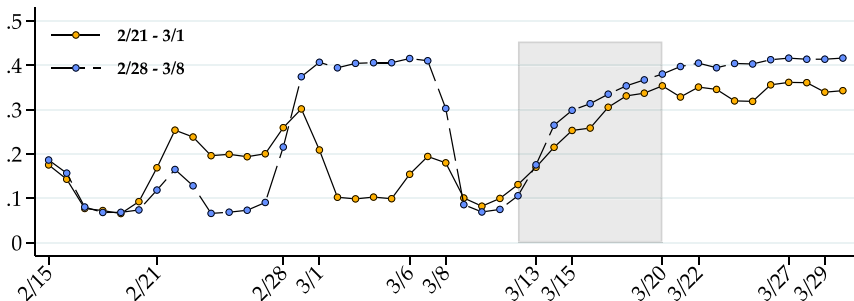
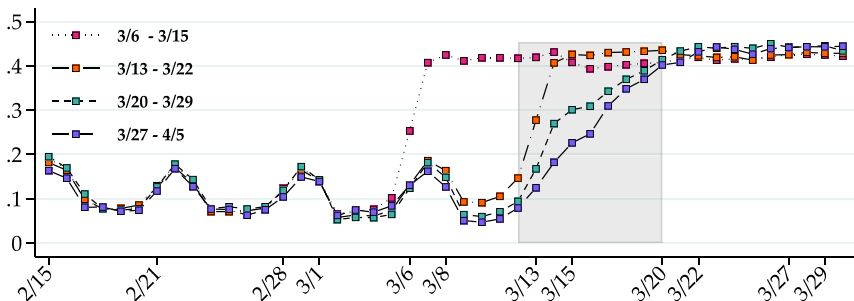B. Share of devices more than 50km from home (Late Spring Breaks)

Fig. 2. Effect of University Spring Break Timing on Student Travel. Notes: Each panel plots the share of devices more than 50km from home by early versus late spring break status. Home is the university CBG and is defined as the primary location of the device at night over a six week period. The shaded regions denote the dates in which most universities suspended in-person classes. Device data are from SafeGraph.

A. Three-day exponential growth rate of confirmed COVID-19 cases
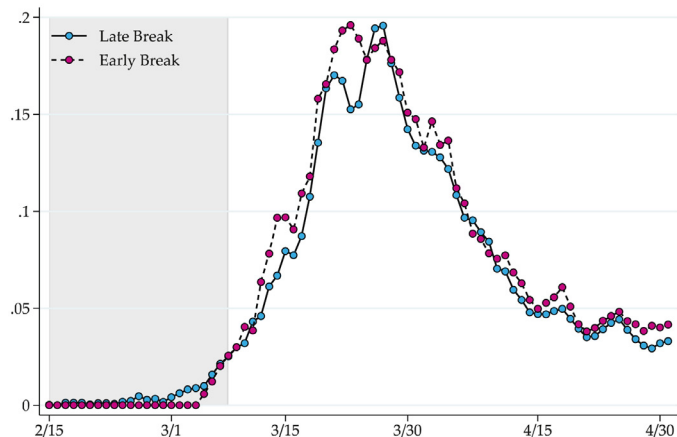
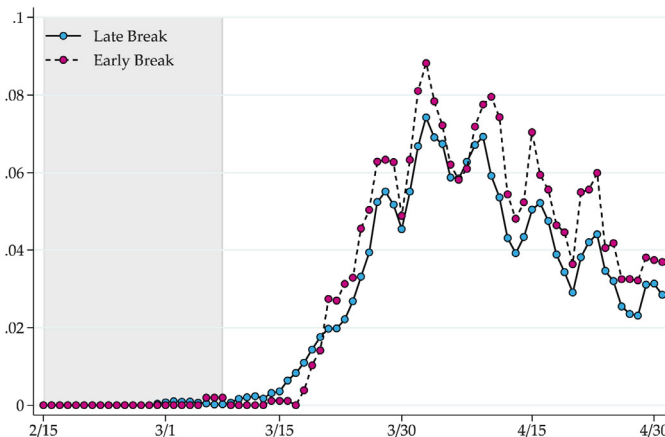B. Three-day exponential growth rate of confirmed COVID-19 mortality

Fig. 3. Evolution of COVID-19 Case and Mortality Growth Rates for Early Versus Late Spring Break Counties. Notes: Each panel above plots the average three-day exponential growth rate of either confirmed COVID-19 cases or mortality separately for early versus late spring break counties. Early spring break counties are defined as counties with more than 25% of the college student population having a spring break which ends before March 9th (120 counties). Late spring break counties are counties with fewer than 25% of the county college student population with early spring breaks (635 counties). The shaded region denotes the early spring break period ending on March 8th. Outcome data come from the New York Times. We also replicate this plot for the level of both confirmed cases and mortality in Figure A.3 to show how the two groups diverge over time.

left campus (either at the start of spring break or upon the suspension of in-person classes) and did not return to campus. Consequently, counties with universities that have early breaks faced large inflows of potentially infected university students returning from spring break prior to the suspension of in-person classes while areas with universities with later spring breaks did not face this influx of potentially infected college students.

Fig. 3 shows the evolution of the growth rate of COVID-19 confirmed cases and mortality separately for early and late spring break counties. We model the daily exponential growth rate similarly to Bursztyn et al. (2020) and Courtemanche et al., 2020 as $\frac{\ln(y_t+1)-\ln(y_{t-k}+1)}{k}$, using the k day growth rate in order to smooth the daily exponential

growth rate.[19] We add one unit to each count within each logarithm to handle observations with zeros.[20] Panel A shows that late break counties had a small increase in the growth in confirmed cases while the early break counties remained on spring break. However, once early break university students return to campus, the growth rates deviate such that the early break counties exhibit exponential growth rates

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[19] Due to day of the week and clustering effects, daily growth rates exhibit a saw-tooth pattern in which a spike in one day causes a decline in the next day's growth rate.

[20] Our results are robust to using smaller adjustments to the dependent variable as well as using percent changes in outcomes instead of log differences. In addition, we estimate a Fixed Effects Poisson specification using case and mortality counts in Appendix A.

almost four percentage points higher than the late break counties. This initial divergence is likely due to the primary detection of spring break travelers returning to the local area and testing positive for COVID-19. After March 15th, the growth rates largely converge with the early break counties maintaining higher growth rates until a second divergence occurs roughly two weeks after the end of spring break. Since the average incubation time for COVID-19 is 6.4 days (Lauer et al., 2020), this timing is consistent with secondary spread whereby the infected spring break travelers spread infections to people on campus and in the local community. After this second divergence from secondary spread peaks, the early and late break counties largely converge to similar growth rates, likely due to universities suspending in-person classes and students leaving the local area.

Panel B shows a similar pattern for the growth rate of mortality. However, since university-aged students face very low mortality-risk, the initial divergence in mortality growth rates is much smaller. On the other hand, the growth rate of mortality associated with secondary spread is much larger and this divergence is maintained throughout the time series.[21] This pattern is additional evidence that, although college students face little internal risk of COVID-19 mortality, they exhibit very high social costs due to potential spread to more vulnerable populations.

Although this divergence is readily apparent in the comparison of means, we proceed to statistically test whether counties with more early spring break college students trended differently in COVID-19 outcomes by estimating an event study specification. The coefficients from the event study specification capture the dynamic nature of the effect of university study travel in each period relative to students returning to campus. Similar to Courtemanche et al., 2020, we use repeated seven day growth rates in order to preserve the cyclical day-of-week effects across the parameters. Our preferred event study specification is,

$$y_{ct} = \sum_{j \in \{[-2,5], j \neq 0\}} \left[\gamma_j \mathbf{1} \cdot \{ j = T + t \} \times \text{EarlyBreak}_c \right]$$
$$+ \delta_c + \alpha_t + \phi \text{EnrollQuartile}_c \times \alpha_t + u_{ct} \tag{1}$$

where y_{ct} is a weekly exponential growth rate for county c during week t (three weeks before and including March 8th and five weeks after March 8th).[22] As described above, we define EarlyBreak_c as a binary variable equal to one for counties with at least 25% of college student enrollment having spring breaks ending prior to March 9th. Each γ_j parameter estimates the average difference in the exponential growth rate for an outcome between early and late break counties during the week j relative to March 8th. We include $\text{EnrollQuartile}_c \times \alpha_t$, enrollment quartile by week fixed effects, to account for any differential effects that student enrollment might have on COVID-19 cases over time. We also include fixed effects for each county and for each week and we present standard errors which are clustered at the county level.[23] In Appendix A, we show that all of the results from the estimation of Eq. (1) are robust to other critical thresholds of pctEarlyBreak_c, the inclusion of state by week fixed effects, a fixed effects Poisson specification, and the removal of various outlier counties.

In accordance with the reduced form results in Fig. 3, we expect for the difference in the growth rate of cases to be largest for the first two weeks after the early spring break period ends and then subsequently decline. On the other hand, it should be the case that γ_j for the mortality outcomes is not significantly different from zero until week three from the early break and beyond.[24]

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[21] Figure A.3 replicates this plot for the levels of cases and mortality per capita.

[22] We have also modeled the main outcome as a standard percentage growth rate and the results are qualitatively similar. In Appendix A, we estimate a Fixed Effects Poisson model which uses counts of confirmed cases and mortality as the outcome variable.

[23] Results are robust to clustering at the state level. This might be appropriate if one is concerned about unobserved error correlation across counties within the same state over time.

[24] This timeline comes from the average incubation of 6.4 days (Lauer et al., 2020) and the average time from exhibiting symptoms until death (conditional on death) of 18.5 days (Zhou et al., 2020).

5. Results

Fig. 4 plots each γ_j coefficient and confidence interval from the estimation of the event study specification. For both outcomes there is no statistical difference in growth rates between the early and late spring break counties in the two weeks prior to March 8th. However, there is a sizable and statistically significant difference in the exponential growth rate between early and late break Counties in the two weeks after March 8th. In the first and second week after early break students returned to campus, the local county experienced exponential growth rates 2.1 and 3.6 percentage points larger than the late break counties, respectively. This pattern echoes the trend presented in Fig. 3 in which early spring break counties have higher growth rates while university students remain in the local area, maintain higher growth rates the week after students leave campus (suggesting secondary spread of infections), then ultimately converge to growth rates similar to late break counties.

The effect of spring break student travel on mortality is presented in Panel B which suggests a similar but delayed pattern. There is no statistical difference in the growth rate of mortality between early and late spring breaks until the week after March 8th. This estimate suggests that late spring break counties experienced a slightly higher growth rate in mortality.[25] However, the early spring break counties begin to overtake the late spring break counties by the second week. By the third week after March 8th, early spring break counties exhibit higher growth rates in mortality of at least 1.2 percentage points, the last of which is statistically significant at the 10% level.

The results in Fig. 4 represent the average effect of increased college student travel on local COVID-19 contagion. However, university students use their spring vacation to travel to a myriad of destinations. At some universities it is common for students to travel by vehicle within-state, while at others it is common for students to fly nationally or internationally. To investigate this heterogeneity, we use SafeGraph data to partition the early spring break sample to include only the counties which exhibit travel patterns which are likely to have a higher risk of contracting an infection. Specifically, we focus on the following four travel patterns: 1) air travel, 2) cruises, 3) travel to/through New York City, and 4) travel to/through beach destinations in Florida.[26] For each of these destinations or modes of travel, we partition the sample of early spring break counties into above and below median visitation to each destination or mode of travel by university-residing devices in the SafeGraph data.[27]

We suspect that university students who travel by air are more likely to encounter other infected individuals and are more likely to travel to international destinations. Next, as evidenced by the high infection rates on the Diamond Princess and Ruby Princess cruiseliners, we also explore whether universities with higher than average trips on cruises had higher infection spread when they returned to campus (Rocklöv et al., 2020). Given that Kuchler et al. (2020) find social connectedness to New York City is associated with greater COVID-19 spread, we cut the treated sample to include counties with above median student spring break travel to New York City. Lastly, we consider universities that had above median travel to the top ten Florida destination counties by all universities.

Fig. 5 repeats the results from Fig. 4 also plotting the event study parameters from each of the four separate heterogeneity analyses. For the weeks prior to March 8th, there remains no statistical difference between early and late spring break counties for any of the subsamples of treated counties. However, the early break universities with above-

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[25] This is likely driven by the early outbreaks in Seattle and the San Francisco Bay area which are both late spring break counties.

[26] These counties are selected using the top 10 most visited counties by university-residing devices. They include Broward County, Orange County, Miami-Dade County, Lee County, Hillsborough County, Palm Beach County, Seminole County, Pinellas County, Osceola County, and Polk County.

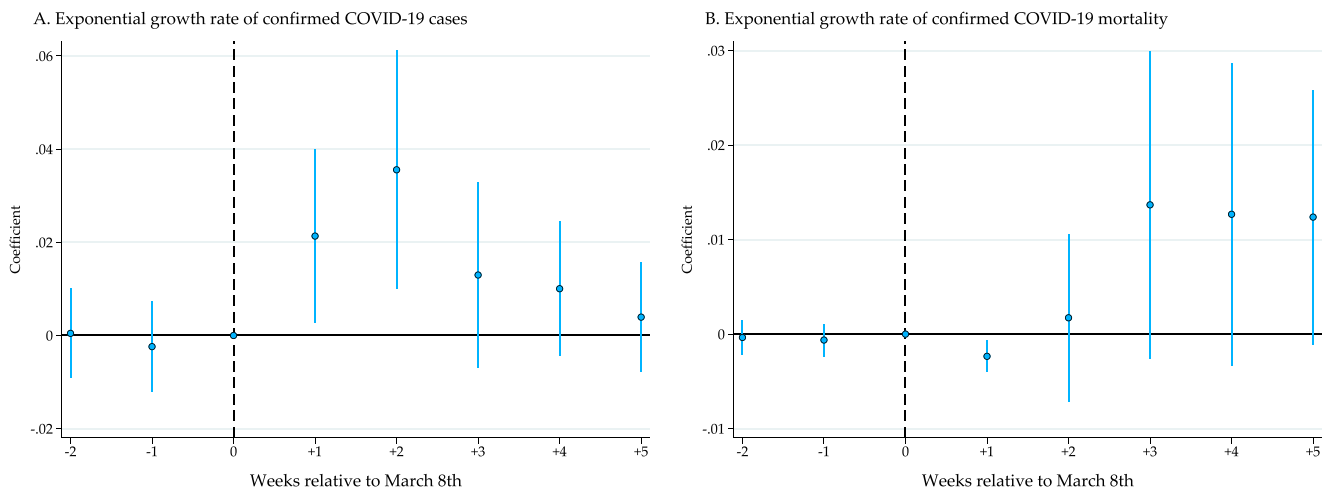[27] The construction of these variables is described more completely in Appendix A.

Fig. 4. Event Study Estimates for the Impact of Spring Break Travel on COVID-19 Cases and Mortality. Notes: Each marker plots a coefficient estimate of γ_j from the event study specification defined by Eq. (1). Vertical bars represent the 95% confidence intervals derived using standard errors clustered at the county level. Each outcome observation is a county's weekly exponential growth rate. Outcome data come from the New York Times.
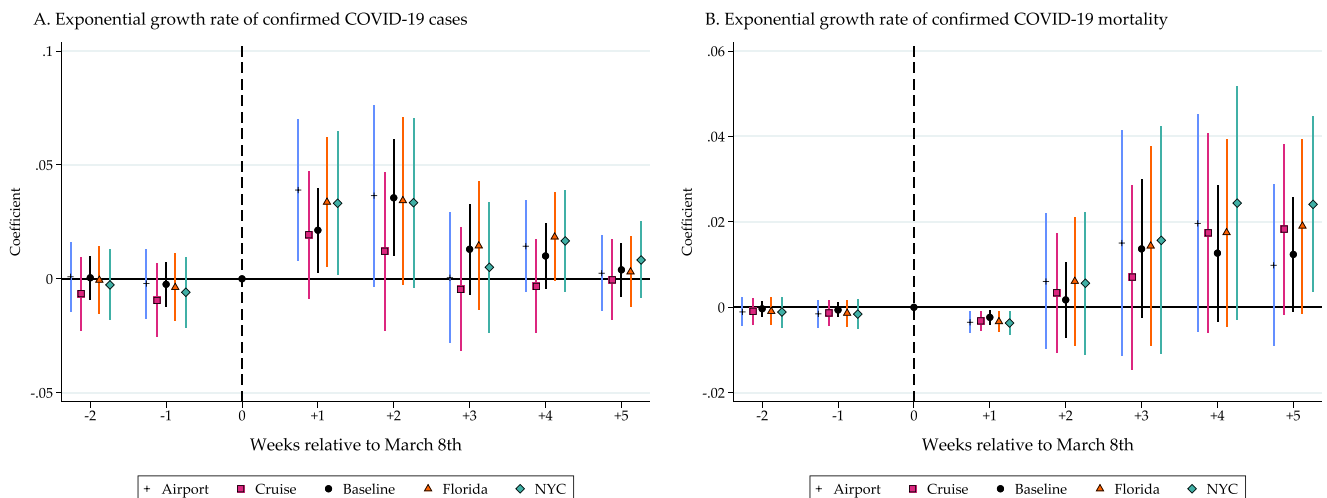

Fig. 5. Event Study Estimates: Heterogeneous Impact by Mode and Destination of Travel. Notes: Each marker plots a coefficient estimate of γ_j from the event study specification where the marker in the legend denotes the heterogeneity subsample used for treatment counties. Vertical bars represent the 95% confidence intervals derived using standard errors clustered at the county level. Each outcome observation is a county's weekly exponential growth rate. Outcome data come from the New York Times.

median travel via air, to Florida, and to New York City show much larger effects in the first week after students return than for the sample of all early break counties. Counties with a university with a large share of air travel had far higher growth rates than the average early break county with a point estimate almost twice that of the overall early break sample (0.039 compared with 0.021). Both travel to Florida and travel to New York City are also associated with higher growth rates than other early break counties with point estimates near 0.033. On the other hand, travel via cruiseliner is associated with only a slightly lower growth rate than other early break counties. In the second week after students have returned, all point estimates besides travel via cruiseliner are similar. Since this week is associated with secondary spread rather than primary infection, it should be the case that the growth rate from week one to week two does not depend on the mode of travel or destination since the primary infection is already accounted for in the week one growth rate. After week two (when most students left campuses after the suspension of in-person classes), the growth rate in cases converges to the late spring break counties and no estimate is statistically different from zero.

Panel B repeats this exercise for the exponential growth rate for mortality. Since the college students who were traveling during spring break have relatively low risk of mortality, there should be no significant divergence in mortality growth rates by mode of travel or destination since the growth in mortality is likely due to secondary spread. Aside from slightly larger estimates for travel to New York City, the estimates are largely similar across the weeks and heterogeneity samples. These results are consistent with the findings above for cases: travel to high risk areas causes more infection of college students prior to returning to campus and these students spread infections to the local area causing an increase in confirmed cases and a delayed increase in mortality.

6. Spring break timing and viral infections prior to COVID-19

While the main focus of this study is the impact of college student travel on COVID-19 spread, the mechanism more broadly applies to other communicable illnesses. While Adda (2016), Ryu et al. (2020), and Simpson et al., 2019 find that influenza spread is correlated with
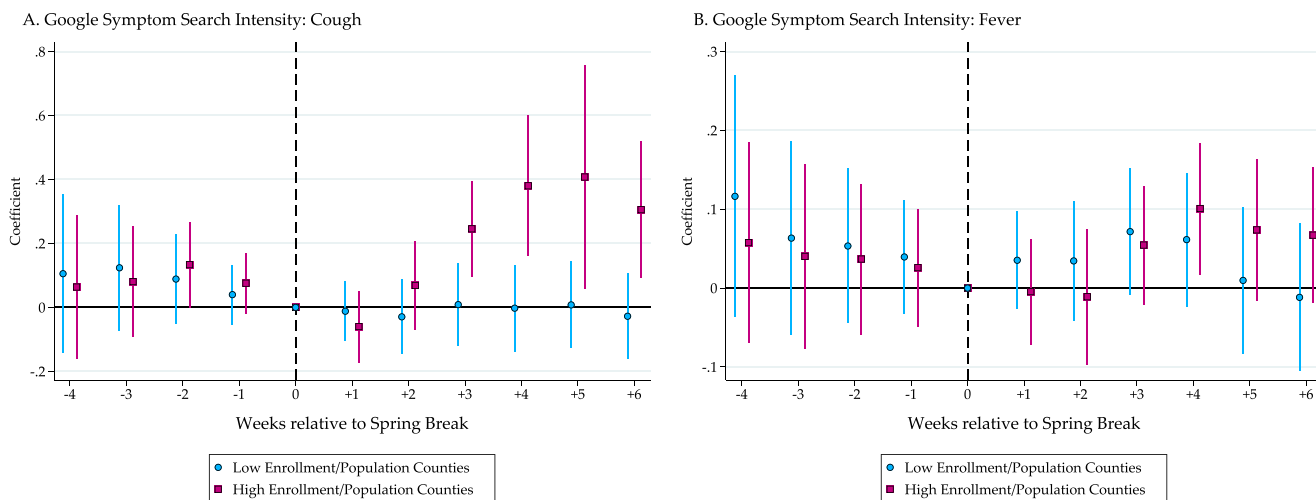
Fig. 6. Event Study Estimates for the Impact of Spring Break Travel on Google Symptom Search Intensity Prior to COVID-19 Notes: Each marker plots a coefficient estimate from the event study specification described in Eq. (2). Each outcome is a Google search intensity measure for either cough or fever at the county-day level. The sample includes counties with a single university in our sample plus all adjacent counties with no universities. Blue circles denote coefficient estimates from the specification in which all adjacent non-university counties are included along with single university counties with below median college student enrollment relative to the county population. Pink squares denote coefficient estimates from the specification in which all adjacent non-university counties are included along with single university counties with above median college student enrollment relative to the county population. Vertical bars represent the 95% confidence intervals derived using standard errors clustered at the county level.

K-12 school calendars, there is little evidence showing how university breaks impact the spread of viral infections. To more generally examine whether universities contribute to infection spread, we study the relationship between spring break timing and illness symptoms *prior to the COVID-19 pandemic*. We collect dates for the 2019 spring break season for counties with a single university in the main sample.[28] We also construct a comparison sample containing all adjacent counties that do not contain a university in our sample. To proxy for illness spread, we use the Google COVID-19 Search Trends Symptoms Dataset which contains daily county level internet search intensity for various symptoms prior to the COVID-19 pandemic (Google, 2020). We focus on the two viral illness symptoms that are most commonly searched in the data: cough and fever.[29]

We estimate an event study specification that compares single-university counties to adjacent counties in the weeks relative to the university's spring break week:

$$y_{cdt}^s = \sum_{j \in \{[-4,6], j \neq 0]\}} \left[\gamma_j^s 1 \cdot \{j = T + t\} \times \text{BreakWeek}_{ct} \right]$$
$$+ \delta_c + \alpha_t + \phi \text{PopQuartile}_c \times \alpha_t + u_{cdt} \qquad (2)$$

In this specification, y_{cdt}^s is the relative search intensity for symptom s in county c on day d contained in week t. BreakWeek$_{ct}$ is a binary variable equal to one when county c's university has its spring break during week t. Each γ_j^s coefficient captures the relative difference in search intensity for symptom s between a university county and a non-university county j weeks relative to spring break after accounting for county (δ_c), week (δ_t) fixed effects, and population quartile by week effects (ϕPopQuartile$_c \times \alpha_t$).[30] We estimate this specification separately

for two samples by splitting university counties into above and below median student enrollment relative to the county population.[31]

Fig. 6 reports the results from estimating Eq. (2) for cough and fever search intensity in panels A and B, respectively, separately for low and high enrollment to population ratio counties.[32] For both the low and high enrollment counties and for both symptoms, there is no statistical difference in the trend in search intensity between university counties and non-university counties prior to students leaving for spring break. However, after students return from spring break there is a divergence between high enrollment university counties and both low enrollment university counties and non-university counties for the search intensity for cough symptoms. Across both symptoms, there is no effect of spring break return for counties with a smaller ratio of college students, but there is an increase in search intensity in high enrollment counties relative to non-university counties that peaks between four and five weeks after spring break. This increase represents roughly a 6% increase from the mean value of cough search intensity in week five.[33] These results support the mechanism that college student travel during spring break may spread viral infections to the surrounding community even in the absence of a pandemic.

7. Discussion

Using smartphone location data, we show that the timing of university spring breaks had enormous impacts on the travel patterns of university students during the onset of the COVID-19 pandemic. Students who attended universities with early spring breaks were significantly more likely to return to campus after their scheduled spring break than students at universities with later spring breaks. Although anecdotal evidence exists linking spring break travel to COVID-19 cases, we provide the first empirical evidence of causal, nationwide effects. We find an increase in the growth rate of confirmed cases during the two weeks

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[28] We restrict attention to single university counties for two reasons. First, counties without a university (our comparison sample) are more likely to resemble counties with a single university than counties with multiple universities. Second, restricting attention to single university counties allows us to assign a spring break week to the county without aggregating universities to the county level.

[29] Due to privacy concerns, there is a large degree of missing data for various symptoms in the dataset. We focus on cough and fever since data on these symptoms are missing for only 1.6% and 10% of observations in our sample, respectively. This is compared to symptoms such as pneumonia, bronchitis, nasal congestion, and upper-respiratory infection which have missing rates of 55%, 80%, 49%, and 96%, respectively.

[30] We use county population quartiles rather than college student enrollment quartiles since non-university counties do not have college student enrollment.

[31] The median value for the college student enrollment to population ratio is roughly 3%.

[32] The low enrollment sample contains all non-university counties and the below median enrollment ratio single-university counties. The high enrollment sample contains all non-university counties and the above median enrollment ratio single-university counties.

[33] The mean search intensity value for high enrollment university counties is 6.4 compared to a point estimate in week five of 0.4.

following the end of spring break. As a result of the temporary increase in case growth rates, early spring break counties had 20% higher cases per capita than late spring break counties by April 30th. Our estimates also provide evidence that mortality growth rates increased four to five weeks after students returned from spring break.

Recognizing that the mode and destination of travel affect infection risk, we link smartphone location data to geospatial datasets for airports and cruise ship ports to analyze spring break destinations and modes of travel for college students. While estimates suggest that students who traveled to airports had a greater than average impact on COVID-19 cases, we do not find any additional effect for the universities with more travel to cruise ship ports. Universities with students who traveled to New York City and to popular Florida destinations faced almost double the risk of primary infection.

We find that university students played a role in initial COVID-19 contagion, although their contribution to further spread remains uncertain. On one hand, our estimates may be an upper-bound for the risk universities face during the pandemic since the analysis uses data from the initial onset when mask usage was rare, population immunity was near zero, and NPIs had not yet been adopted. On the other hand, the number of active cases at the beginning of the Fall 2020 semester was far greater than in March 2020, which suggests the probability of encountering an infected individual was far higher when students returned to campus.[34] As a result of these opposing effects, our estimates may be in line with the potential risk universities face when inviting students back to campus during the pandemic.

Our findings can also help inform policy after the COVID-19 pandemic subsides. In addition to results from within the pandemic, we present evidence that college student travel during spring break also contributed to the spread of communicable illnesses *prior to the COVID-19 pandemic*. In the weeks after students returned from spring break, internet searches for common symptoms of viral infections increased in counties with a large college student population share relative to neighboring counties without a university and counties with fewer college students. We interpret the increase in searches for illness symptoms as a proxy for actual illness, but future research may effectively link college student travel to confirmed cases of viral illnesses besides COVID-19.

We highlight the role universities play in making consequential decisions that can benefit the health of surrounding communities by altering the behavior of nearly 8 million undergraduates nationwide. The reduction of long-distance student travel and social interactions with the surrounding community via university NPIs would complement state and local government NPIs. These policies could enable universities to welcome students back to campus and offer in-person classes throughout the remainder of the COVID-19 pandemic with smaller external costs to surrounding communities. These results suggest universities can reduce the spread of viral infections, like COVID-19 and seasonal influenza, by implementing low-cost NPIs during the spring break season, especially as students return to campus following travel.

CRediT authorship contribution statement

Daniel Mangrum: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing - original draft, Writ-

ing - review & editing. **Paul Niekamp:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing - original draft, Writing - review & editing.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2020.103311.

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