A Online Appendix

A.1 Mobility Data

We match Safegraph mobility data to universities using the Census Block Group (CBG) associated with each university in the sample. The "home" of each device in the Safegraph data is defined as the 153 by 153 meter square in which the device predominately resides at night over a six week period. The devices which reside within the university CBG are almost surely university students, however this categorization is likely an underestimate of university students. Since the CBG is a small geofence, this categorization is unlikely to capture off-campus residing students in the sample.

We also use device flow counts from a home CBG to destination CBGs to track the travel of university students to various spring break destinations. First, we collect geospatial information on the top 200 airports in the United States by commercial enplanement volume. We then use the GPS coordinates of each airport to assign each airport to its corresponding CBG.[35] We then create counts of the number of visits to any of the top 200 airports by devices which call a university home during the week of February 29th through March 8th.[36] We also replicate this process for cruise ship ports using the same methodology. Lastly, we construct similar counts for university-residing devices that visit either New York City (any of the five NYC counties) and for the top 10 Florida destination counties during the week of February 29th through March 8th.[37] We exclude any visits to these counties from universities within the same county as these device counts do not measure travel.

After constructing these visit counts, we create a ratio for each university of the number of device-day visits to each of the four destination categories to the average number of active university-residing devices over the course of February 29th through March 8th. Since a device can make multiple visits over the course of the week, the ratio is bounded below by zero *but is not bounded above by one*. We then find the median of these ratios across the sample and create an identifier denoting universities that are above median for each ratio.[38]. We then collapse this to the county

[35] We randomly inspect this assignment and for all inspections, the CBG for each airport contains only the airport geofence and does not contain any commercial or residential areas near the airport. This is largely systemic due to the methodology of CBG design (United States Census Bureau, 2020).

[36] Since a device can visit multiple airports in a day, there may be more visits than active devices.

[37] These top ten destination counties are Broward County, Orange County, Miami-Dade County, Lee County, Hillsborough County, Palm Beach County, Seminole County, Pinellas County, Osceola County, and Polk County

[38] If the median for the ratio is zero, the identified sample will contain fewer than half of the universities

level by creating an identifier for whether a county that was previously denoted as an Early Break county also had at least one of these above median higher risk travel universities. These identifiers are used in the heterogeneity analysis in Section 5.

We thank SafeGraph for providing Social Distancing Metrics data.

> "SafeGraph, a data company that aggregates anonymous location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group."

A.2 Robustness

We estimate a variety of robustness checks to demonstrate the robustness of our general finding. We report the results of these robustness checks in Figure A.1. Across each of these specifications, the qualitative conclusion from our main results remain unchanged. We briefly describe the motivation for each robustness check below.

Panel A. We vary the critical threshold for the definition of a treated county.

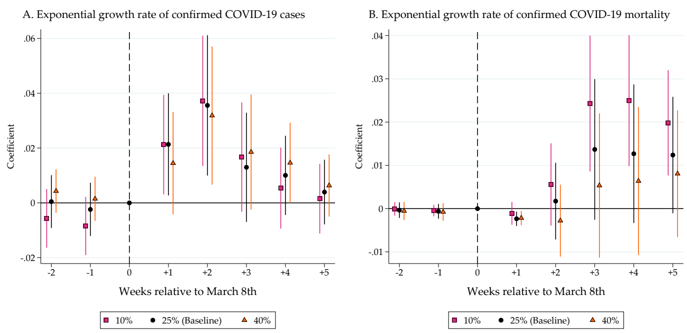
Panel B. We make three sample exclusions to show robustness to 1) low density of treated units, 2) high density of treated units, and 3) outliers in population density for treated units.

Panel C. We include state-by-week fixed effects to account for state level NPIs and variation in temperature in early versus late spring breaks. We also omit the earliest spring break universities since they exhibit somewhat different travel patterns.

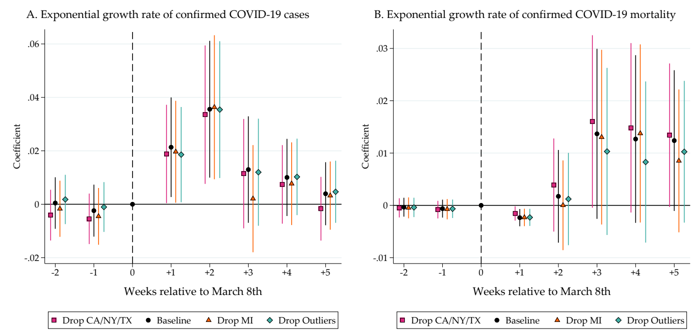
Panel D. We estimate an event study specification using a Fixed Effects Poisson model. This specification uses total case and mortality counts as the outcome variable.

Figure A.1: Robustness for Event Study Estimates

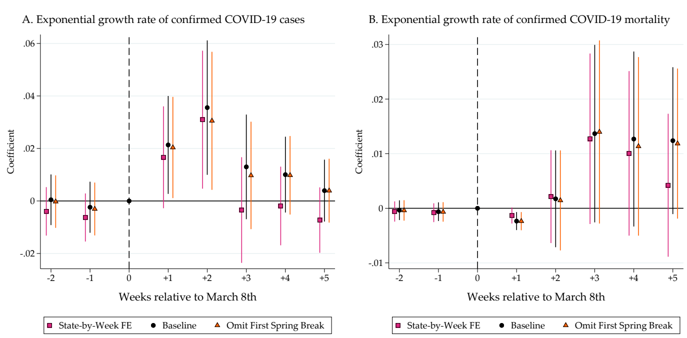
(a) Various Thresholds of pctEarlyBreak



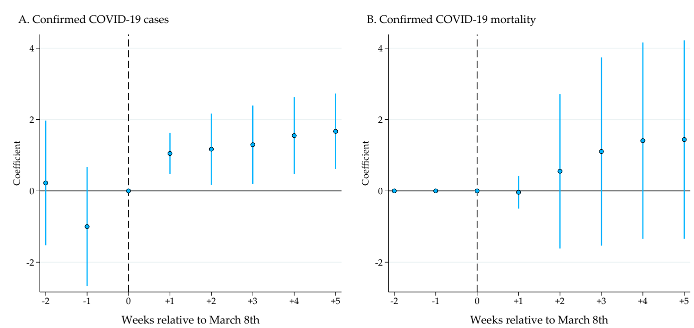
(b) Select Sample Exclusions



(c) State-by-Week Fixed Effects and Omitting Initial Spring Break Week



(d) Event Study Estimates Using Fixed Effects Poisson Specification



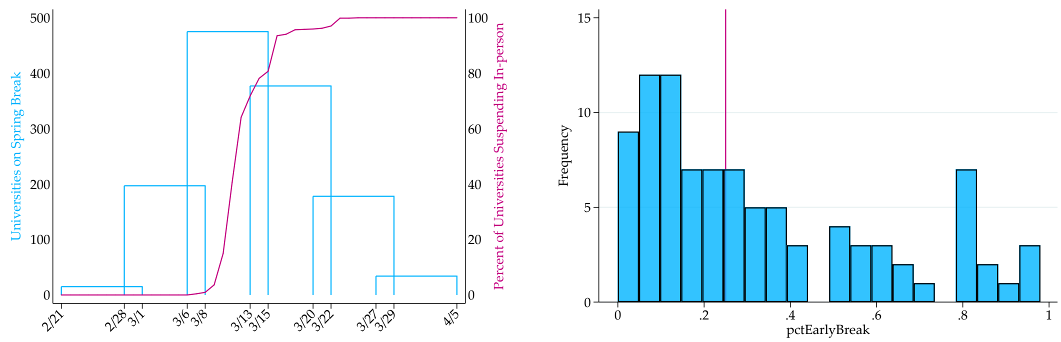
Notes: Each marker plots a coefficient estimate of γ_j from the event study specification with the described alteration. Vertical bars represent the 95% confidence intervals derived using standard errors clustered at the county level. For Panels A, B, and C, each outcome observation is a county's weekly exponential growth rate. For Panel D, each outcome observation is a county's total case or mortality count. Outcome data come from the New York Times.

A.3 Miscellaneous Tables and Figures

Figure A.2: Histograms of Spring Bring Dates and Percent of Early Beak College Students

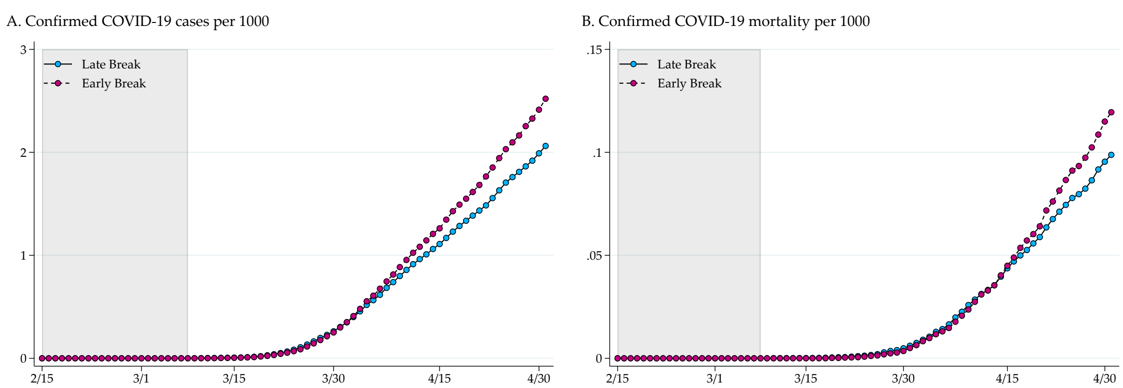
(a) Spring Break Dates and Suspension of In-person Classes

(b) Percent of Early Break College Students



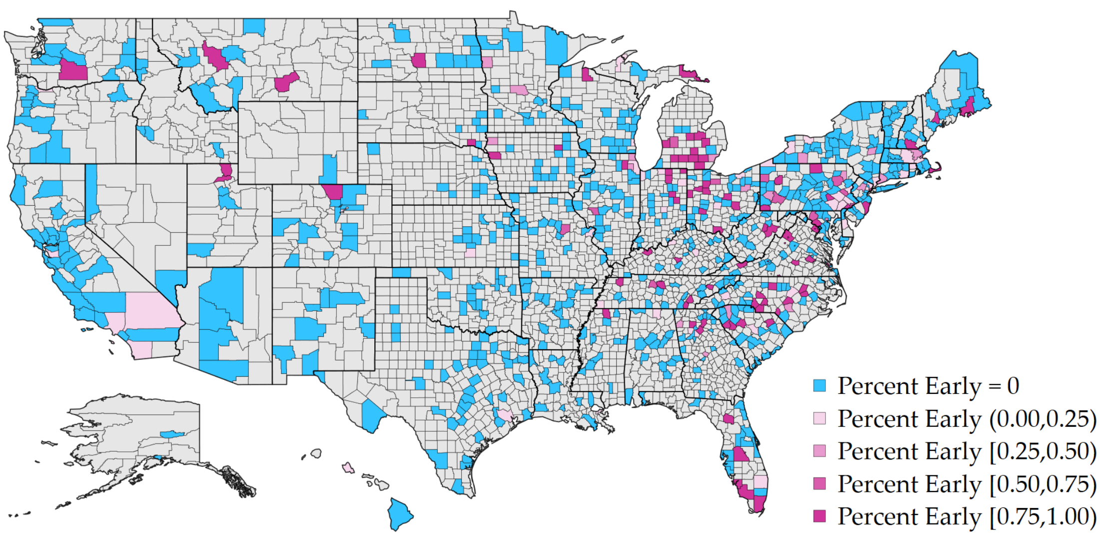
Notes: Panel A plots a histogram of the number of universities on spring break by each week. We also plot the percent of universities suspending in-person classes for a subsample of our university sample. This collection is not exhaustive, but the overall trend is consistent with the dates described in Marsicano et al. (2020). Panel B plots a histogram of our pctEarlyBreak variable at the county level. We omit 588 observations where pctEarlyBreak is equal to zero and 74 observations where pctEarlyBreak is equal to one.

Figure A.3: Evolution of Cases and Mortality per 1000 for Early and Late Spring Break Counties



Notes: Each panel above plots the average total confirmed COVID-19 cases or mortality counts per capita 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.

Figure A.4: Counties by Percent of College Student Enrollment with Early Spring Breaks



Notes: Each county is shaded according to the percent of the college student population that had a spring break ending before March 9th. Gray counties do not contain a university in our sample. Blue counties did not have any early spring break counties in our sample. The various shades of pink represent bins of pctEarlyBreak. Our baseline specification defines an early spring break county as having at least 25% of the county's college student population having an early spring break (last three bins).

Table A.1: Balance Tables: Comparison of Early vs Late Units

(a) Counties

Variable	(1) Late Break	(2) Early Break	(3) Difference
Population Estimate 2018	318,904.2	305,951.9	-12,952.3
	(718,913.0)	(421,613.7)	(68,022.5)
Republican Voteshare 2016	51.9	53.5	1.6
	(15.8)	(15.8)	(1.6)
University Enrollment	10,270.4	8,703.8	-1,566.6
	(16,592.7)	(12,634.7)	(1,602.1)
Percent Non-Hispanic White	72.1	73.4	1.4
	(19.9)	(18.5)	(2.0)
Percent Adults Less Than HS	11.2	11.4	0.2
	(4.7)	(4.4)	(0.5)
Percent Adults With Bachelors	29.6	28.3	-1.2
	(9.7)	(10.8)	(1.0)
Unemployment Rate 2018	3.9	3.9	0.0
	(1.1)	(1.0)	(0.1)
Median HH Income 2018	57,639.8	58,664.0	1,024.2
	(14,803.6)	(15,848.2)	(1,496.0)
Average Feb Temp	38.3	36.8	-1.4
	(11.2)	(11.0)	(1.1)
Average March Temp	48.7	47.1	-1.6
	(10.5)	(9.8)	(1.0)
Average April Temp	52.2	50.4	-1.8**
	(8.8)	(8.5)	(0.9)
Percent Male	49.3	49.3	-0.1
	(1.4)	(1.4)	(0.1)
Primary Care Physicians pc	91.7	93.5	1.7
	(15.3)	(12.6)	(1.5)
Percent Of Population 65 Plus	16.8	17.3	0.5
	(3.6)	(3.6)	(0.4)
Population Density	584.2	897.9	313.7*
	(1,812.3)	(2,112.5)	(186.1)
Observations	635	120	755

(b) Universities

Variable	(1) Late Break	(2) Early Break	(3) Difference
Full-time Enrollment	6,004.6	4,136.3	-1,868.3***
	(7,837.7)	(6,567.1)	(572.0)
Percent In-State	69.2	68.4	-0.8
	(25.2)	(22.3)	(1.8)
Percent of Aided w Fam Inc 0-30K	34.6	32.6	-2.0**
	(13.4)	(12.2)	(1.0)
Percent of Aided w Fam Inc 110K plus	21.5	22.0	0.5
	(12.0)	(12.0)	(0.9)
Avg Fam Inc Dependent Students	74,674.4	76,468.8	1,794.4
	(23,007.4)	(21,969.8)	(1,732.4)
Percent of Financially Indep Students	21.1	21.5	0.4
	(14.9)	(15.6)	(1.1)
Percent w Parents HS Ed	30.1	31.1	1.0
	(8.0)	(7.6)	(0.7)
Percent Female	57.7	59.1	1.4*
	(9.8)	(11.1)	(0.8)
Percent Married	7.6	8.8	1.1**
	(6.4)	(6.8)	(0.5)
Percent First Generation	31.5	31.7	0.2
	(10.1)	(9.5)	(0.8)
Observations	1,113	213	1,326

Notes: The table above reports the means and standard deviations for relevant observable characteristics at the county level by early versus late spring break counties. Early spring break counties are defined as counties with 25% or more of the college population in the county having a spring break that ended prior to March 9th. Column Three reports the difference in means between the two groups. Stars denote statistical significance of a test of a difference in means. *p<0.10, **p<0.05, ***p<0.01