Walking in the University of Memphis: Which College Campuses Opened in Fall 2020?

Nick Huntington-Klein[a,*]

[a] *Seattle University*

Abstract

In Fall 2020, due to the COVID-19 pandemic, colleges faced the unusual decision of whether or not to open their campuses to students, and if so, how extensively. Some colleges opened fully, or near so, while others shifted entirely online. Which attributes explain the level of reopening for US two- and four-year institutions? I use mobile phone location data to produce a continuous measure of the level of reopening at each college. Some college features, such as number of dorms, private status, student racial mix, and out-of-state prevalence predict the degree of reopening. However, external local cues are highly important, with local COVID prevalence, the behavior of nearby large colleges, local political environment, and spatial autocorrelation meaningfully explaining variation in reopening levels.
Keywords:

PRELIMINARY, PLEASE DO NOT CITE

I. INTRODUCTION

In the leadup to the Fall 2020 term, colleges in the United States faced the difficult decision of how much they would open their campuses to students. With the COVID-19 pandemic still ongoing, full classrooms and campus events could be dangerous. Concerns about disease would prove justified when, following the beginning of the fall term in which many colleges

*Corresponding Author. Email: nhuntington-klein@seattleu.edu. Address: 901 12th Ave., Seattle, WA 98122

did allow students back on campus, disease rates jumped sharply in college towns (Watson et al., 2020).

Why did these colleges open as much as they did? Without federal legal requirements to shift fully online, colleges and college systems in many cases were able to determine for themselves the degree to which they would open, and so decision-making can be located at the institutional level. Concerns about students and employee health and spread of the disease had to be weighed against clear valuable incentives for reopening (Wrighton and Lawrence, 2020).

In this paper I look at institution-level information to describe which colleges more extensively reopened their campuses to students and visitors in Fall 2020. Descriptions of which attributes differ across levels of reopening give a sense of which factors decision-makers paid attention to when planning their reopening or in shaping the policy preferences of administrators making reopening decisions. It is worth knowing, for example, whether reliance on student tuition revenues or political considerations, neither of which are relevant for student safety, may be strong predictors of institutional decision-making that could expose large numbers of people to risk, especially if there may be similarly difficult decisions in the future.

There is a fair amount of research on the correlates of institutional decision-making in regards to COVID-19 shutdowns, especially in regards to national governments (e.g. Capano et al., 2020; Toshkov et al., 2020), finding that policymaking capacity and past experience with pandemics are important predictors. In the United States, where strict lockdowns imposed by any level of government have been rare, much of the existing literature has focused on individual behavior, such as social distancing (e.g. Allcott et al., 2020; Baradaran Motie and Biolsi, 2020), or business behavior, such as de Vaan et al. (2020), rather than the decision-making of public institutions.

The closest paper to this one is DeAngelis and Makridis (2020), which looks at reopening decisions in K-12 school districts.[1] Their study focuses on teacher unions as a potential

[1] As of this writing, literature on COVID-19 from all angles is moving extremely rapidly, and it is entirely

determinant of institutional decision-making. They find a negative correlation between union strength and reopening decisions among 835 public school districts in the US.

In application to colleges as opposed to K-12 schools, however, the measurement of reopening is not straightforward. Resources like The College Crisis Initiative (2020) have gathered extensive information about the statements that colleges have made about their reopening, with fifteen different announcement categories like "fully open" and "professor chooses online/in-person". However, translating this into information about how extensive a college's reopening will be requires determining how these options actually compare in terms of openness, as well as unmeasured factors such as how strictly student restrictions are enforced, and what portion of courses are in-person, and featuring what portion of students, if "some" will be in-person.

Instead of using official college announcements, in this paper I use mobile phone location data from SafeGraph (2020) to measure foot traffic on each campus. The difference between foot traffic levels in 2019 and in 2020 is taken as a continuous, sensitive measure of how sharply the campus has been shut down or reopened. For a basic demonstration of how the same announcement may translate into meaningfully different reopening levels, Boston University and Mississippi State University are both listed as "Hybrid" on The College Crisis Initiative (2020).[2] Using the reopening measures described later in the paper, Boston University saw a 68% drop in foot traffic, while Mississippi State saw only a 51% drop. Similarly, San Diego State University (-77%) and Miami University Oxford (-86%) are both listed as "Primarily Online."

Mobile phone location data, and SafeGraph data specifically, has been used in a number

possible that these two paragraphs will be a less-fair characterization of existing research by the time you read it. For this reason, while I do not cite any other paper examining correlates for for college reopenings in the United States in Fall 2020, and have searched extensively for one, I cannot confidently claim to actually be novel in that regard.

[2] To ensure I looked at institutions of comparable size I looked at their NCAA institution listings, selected one Hybrid college at random (and similarly for Primarily Online), and then selected another institution of the same reopening status with a similar COVID prevalence for comparison. This was non-random selection but non-intentional.

of studies of individual behavior during the pandemic (Goolsbee and Syverson, 2020; Allcott et al., 2020; Bai et al., 2020). Mobile phone data is valuable for this purpose both because some traditional data sources have become less reliable due to COVID-19 restrictions, because it can be collected and made available much more quickly than large-scale survey methods, and because it does not rely on self-report.

Using mobile phone location data to measure the extent of reopening at both two- and four-year colleges, I find, among other relationships, that Fall reopenings were larger at private institutions and institutions with more white and more out-of-state students. Reopenings were sensitive to COVID-19 prevalence, and were smaller in areas with higher case or death rates as of July 2020. Perhaps surprisingly, there was no strong indication that colleges with more prior experience delivering online instruction shut down more heavily. Location matters, as well, in ways that indicate that local informational and political cues are correlated with reopening levels. Degree of reopening displayed high levels of spatial autocorrelation, level of rurality strongly predicted bigger reopenings, and reopening at small institutions is strongly related to reopening at nearby large institutions.

Political environment and local attitude towards COVID-19 was strongly related to reopening. Areas with more conservative political representation had bigger reopenings, beyond what could be explained by the urban/rural divide. Areas in which higher proportions of people self-reported always wearing a mask in public had smaller reopenings, even though reopening would theoretically be somewhat safer in areas with more consistent mask usage.

I also find that the predictors of reopening changed rapidly throughout the year. When measuring the degree of shutdown in April as opposed to Fall, I find that the influence of political environment was vastly reduced, and that the tuition share of revenue was a meaningful predictor.

In all cases, these predictors explained only a modest portion of measured changes in foot traffic. While there are meaningful average differences between institutions related to the above-mentioned variables, the reopening responses for many colleges are explained poorly by observables.

II. DATA

The data for this study come from multiple sources. Perhaps the most unusual source is the SafeGraph cell phone location data used for the dependent-variable measure of how much a college opened its campus. The next sections will describe the SafeGraph data as well as other sources.

II.i. SafeGraph Geolocation Data

Foot traffic data comes from the private data company SafeGraph, and is produced by combining their Core and Patterns data sets, for which full documentation is available at docs.safegraph.com.

The SafeGraph Core data set is a collection of approximately 6 million locations across the United States. Locations are at the level of, for example, a single storefront, and the list of locations focuses on businesses and institutions rather than residential locations.

Each location in the data is tagged by its latitude and longitude, and is categorized by its function using a NAICS code. In this study, I focus on the 18,293 locations tagged with the four-digit NAICS codes 6112 (Junior Colleges) and 6113 (Colleges, Universities, and Professional Schools). These codes do not include stadiums or university hospitals.[3] Of these locations, 16,395 could be matched to college institutions using methods described in Section III.i.

Approximately 4.1 million of the 6 million locations in the Core file are also in the SafeGraph Patterns file, including all of the locations used in this study. The SafeGraph patterns file uses cell phone location data to provide aggregated counts of visitors to each

[3]Additional analyses will use locations of any NAICS code within a certain distance of the campus' IPEDS-listed location.

location, providing data from the start of 2019. This study uses data from January 2019 to mid-September 2020.

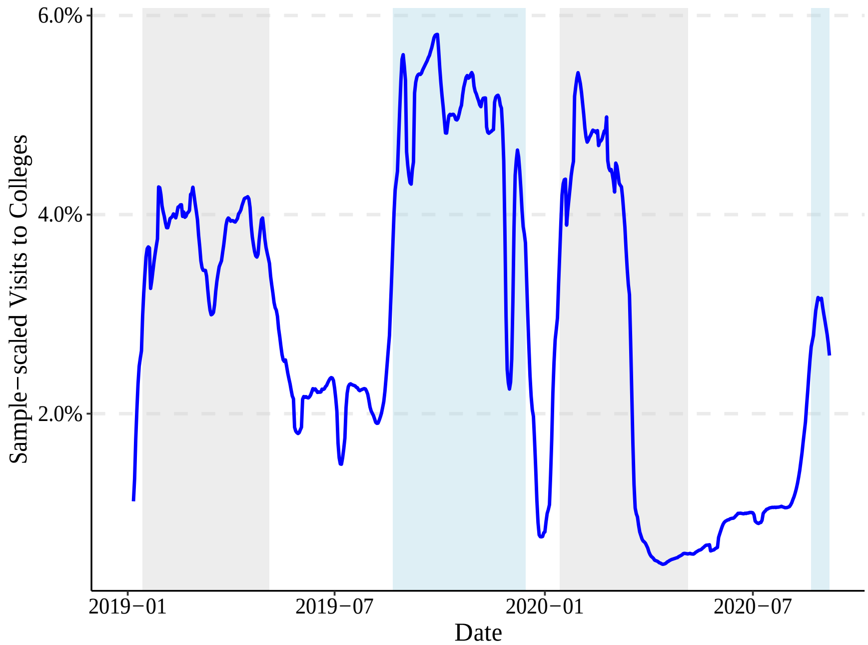
SafeGraph continually increases the number of tracked locations, and removes defunct locations. To avoid the appearance of foot traffic growth on a campus due to the addition of more tracked locations, locations are omitted if they are not present in Patterns in both 2019 and 2020. This further drops the number of locations used in analysis to 15,374.

SafeGraph has access to location data from approximately 20 million devices as of June 2020. The size of the SafeGraph sample itself has changed over time, and so all foot traffic values are scaled by the number of devices in the sample on a given date. To be included in the data, a cell phone user must download one of the apps that licenses location data and has an agreement with SafeGraph, and then agree to that app's terms of service. The apps themselves are not controlled by SafeGraph and include things like video game apps.

A device that is in the panel will report its location any time it pings a cell phone tower. The phone's location is then linked to one of the SafeGraph locations, and this is recorded as a "visit." SafeGraph aggregates these visits for each location over a given time period. For the purposes of this study, an observation for a given location might be expressed as "X device visits were recorded to location Y on the campus of college Z on date A." Then, this is aggregated to the level of associated colleges and universities so that a given observation would be "X device visits were recorded to locations associated with college Z on date A." There is a possibility that some devices are double-counted by visiting multiple locations on the same campus in the same day, but this is kept in as a valid measure of foot traffic on campus.

The fact that SafeGraph participation is based on downloading certain apps means that there is selection into the sample. Since there is no information about individual devices, I do not attempt to correct for this bias. However, all foot traffic values used in this study are taken within-location or within-groups-of-locations. Then, these within-changes are compared across campuses. So, it is not necessary to assume that there is no endogenous

Figure 1: Aggregated Foot Traffic to Colleges in SafeGraph Data, 2019 and 2020



(a) Seven-Day Moving Average. Shading indicates rough outlines of Fall and Winter/Spring terms begin and end. Y-axis is percentage of devices in sample that visited a location with NAICS code 6112 or 6113 on that day.

sample-selection pressure. Rather, it is necessary to assume that any change in endogenous sample-selection pressures over time was consistent across campuses.

There are reasons to doubt the accuracy of the foot traffic measurement used here—the list of locations may not cover the entire campus area, and some locations may have been included despite not actually being affiliated with an IPEDS college. To provide an initial check on the quality of the measurement, in Figure 1a I test whether foot traffic aggregated across all institutions appears to change over time as would be expected given common college operation times.

Figure 1a largely matches expectations. Keeping in mind that dates of instruction vary across campuses, foot traffic is high during the periods that correspond to the beginning and end of typical university Fall and Winter/Spring terms. Dips corresponding to Thanksgiving and spring break are clearly visible. The COVID campus shutdowns in Spring 2020 are stark and clearly visible, as is the return of students to campus in late August 2020.

One thing to note is that visits are higher in January and February of 2020 than in

January and February of 2019, about a 21% increase, suggesting either that actual foot traffic was up, or that college-goers made up a higher proportion of the SafeGraph sample in 2020 than in 2019. Because of this, the aggregate change from Fall 2019 to Fall 2020 is likely to understate the actual decline in foot traffic, and so it is important to compare these changes between colleges, as will be done in the paper.

II.ii. Compiled Data

Independent variables for the paper come from more traditional sources than the foot traffic data. Data at the institution level comes from the Integrated Postsecondary Education Data System (National Center for Education Statistics, 2020) 2018 and 2019 files for 3,736 US two-and four-year public and private nonprofit colleges. This includes information about enrollment, institution finances, dorm room capacity, makeup of the students, and institutional experience with online courses.

Institution data from IPEDS on campus location (by latitude and longitude), county, and congressional district are used to connect to other sources of data. Latitude and longitude is used to connect each campus to SafeGraph locations, as previously discussed.

The political environment surrounding the college is first measured using electoral outcomes collected by Morris (2020): the share of votes in the college's congressional district that went to Donald Trump in the 2016 presidential election, the party of the congressional representative in that district, and that congressional representative's Common-space Constant DW-NOMINATE scores as calculated by Lewis et al. (2020). This data is available for 3,605 colleges.

DW-NOMINATE is a multidimensional scaling method that uses congressional voting data to estimate a congressperson's ideological standing (Carroll et al., 2009). Common-space Constant DW-NOMINATE operates under the assumption that a congressperson's ideology is constant over their career, and estimates ideology measures based on which congresspeople vote in similar ways. The scaling produces two dimensions. Dimension 1 can be thought of as an economic liberal (negative)/conservative (positive) measure. Dimension 2 can be thought of as representing social liberal (negative)/conservative (positive) ideology.[4]

The last source of political data, which reduces the number of colleges in the sample to 3,483, is specific to local preferences and behavior concerning the COVID-19 pandemic. This is proxied by are county-level average responses to the question "How often do you wear a mask in public when you expect to be within six feet of another person?" Options were "Never", "Rarely", "Sometimes", "Frequently," and "Always." The survey was administered online survey question to roughly 250,000 respondents from July 2 to 14, 2020, and was conducted by Dynata at the request of the New York Times.

Response averages were generated at the census tract level using the 200 nearest responses by ZIP code, weighted by inverse distance, age, and gender. Tract estimates were aggregated to the county level using tract-population weights. County-level estimates are then linked to colleges by county.

County is also used to link colleges to local COVID-19 incidence. Data on county-level cumulative COVID-19 cases and deaths as of March 31, 2020 and July 31, 2020 are from The New York Times (2020). These figures compile reports on confirmed and suspected cases from a large number of different data sources. These estimates are sometimes revised as new information comes in, but this paper uses only estimates for the dates of March 31 and July 31, downloaded on September 1, 2020, and so the chance that these figures will be revised in the future are reduced.

COVID-19 cases and deaths are taken as a proportion of the county population as of 2019. Population figures come from published Census figures. Census information on the percentage of each county that is rural is also included.

The data is then also linked to SafeGraph foot traffic data, using methods described in Section III.i. Some colleges cannot be matched to locations in the SafeGraph data, dropping

[4]The DW-NOMINATE algorithm itself only identifies the two measures that describe how different congresspeople vote. The labeling of the indices is more subjective and is based on the content of the bills that are being voted on.

the number of institutions included to 3,312. Then, because the outcome variable is in terms of percentage growth, I avoid inflated growth based on a low baseline by excluding colleges below the 5th percentile of foot traffic activity in 2019 or that are missing 2019 entirely. To avoid apparent increases that are more likely due to changes in the SafeGraph sample, I also exclude colleges with fall-to-fall growth above the 90th percentile. The 90th percentile is roughly a 90% increase in foot traffic, keeping in mind that, as discussed in Section II.i, absolute growth is overstated by as much as 21% due to the changing SafeGraph sample. The argument for selecting on the dependent variable here is that at this part of the dependent variable distribution, these are not actual large growth rates but rather evidence of poor measurement or idiosyncratic sample composition changes. The combination of these limitations results in a sample of 2,809 institutions before considering missing data.

Table 1 shows summary statistics from the full list of variables collected from IPEDS, as well as the year in which the data was collected. Summary statistics are taken at the institution level after limiting the data to the primary analysis sample.

There are several IPEDS variables of particular emphasis in this paper. The first is dormitories. More than half of all institutions (which includes both two- and four-year institutions) offer dormitories, with an average of roughly one room for every four FTE students. However, the amount of variation in dormitory capacity is very high, with a standard deviation nearly double the mean. Institutions with large dormitory facilities may be particularly interested in opening their campus, since these resources would go largely unused without an open campus.

The second is tuition revenue share, in other words the share of revenues that comes from tuition. Institutions that rely heavily on tuition revenue may be more likely to open, out of fear that enrollment would drop more heavily with a closed campus, stressing the college budget. Unfortunately, there are a large number of missing observations for tuition revenue share, with only 2,296 institutions reporting.

The third is the proportion of students who take online courses. Institutions that already

Table 1: Data from IPEDS

Variable	N	Mean	Std. Dev.	Variable	N	Mean	Std. Dev.
Institutional Information				**Online Experience**			
FTE fall enrollment (k) (2018)	2797	4.18	6.87	Pct. Studs Exclusively Online (2018)	2797	0.12	0.15
Tuition Revenue Share (2018)	2296	0.42	0.27	Pct. Studs Somewhat Online (2018)	2797	0.17	0.17
Part of Multi-institution Org. (2019)	2809			Pct. Studs Not Online (2018)	2797	0.71	0.25
... No	1731	62%		**Students**			
... Yes	1078	38%		Undergrad Pct. (2018)	2797	0.84	0.27
Offers Dormitories (2019)	2809			Asian Pct. (2018)	2797	0.044	0.066
... No	1269	45%		Black Pct. (2018)	2797	0.14	0.18
... Yes	1540	55%		Hispanic/Latino Pct. (2018)	2797	0.14	0.16
Dormitory Capacity per FTE (2019)	2796	0.28	0.46	White Pct. (2018)	2797	0.55	0.24
Private Non-profit (2019)	2809			ANPI/Other/Multi race Pct. (2018)	2797	0.089	0.096
... No	1568	56%		Women Pct. (2018)	2797	0.58	0.16
... Yes	1241	44%		In-State Pct. (2018)	2547	0.79	0.24
Predominant Degree Type (2019)	2809			Out-of-State Pct. (2018)	2547	0.17	0.22
... 2-year	1066	38%		Foreign Pct. (2018)	2547	0.023	0.052
... 4-year or above	1743	62%					

FTE = Full-time equivalent.

have more experience delivering online education at scale may be more prepared to transition to an entirely-online experience. Keeping in mind that these statistics are at the institution level and are not weighted for institution enrollment, the average proportion of students who were fully face-to-face in 2018 was 71%, with 17% taking some online classes, and 12% taking entirely online classes. The amount of variation is high here as well.

Summary statistics for the linked COVID-19 and political variables are in Table 2. Observations are again at the level of linked institutions, so some counties and congressional districts are represented multiple times, and others are not represented at all.

Table 2: Data on Coronavirus and Politics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Disease							
County Cases/k.pop March 31 (NYT, Census, 2020)	2809	0.44	1.03	0.00	0.094	0.39	10.30
County Cases/k.pop July 31 (NYT, Census, 2020)	2809	12.94	8.87	0.22	6.35	18.01	90.83
County Deaths/k.pop July 31 (NYT, Census, 2020)	2809	0.41	0.46	0.00	0.10	0.49	3.84
Political Environment							
Survey: Masks Never (NYT, 2020)	2809	0.046	0.039	0.00	0.02	0.063	0.30
Survey: Masks Rarely (NYT, 2020)	2809	0.048	0.041	0.00	0.019	0.067	0.36
Survey: Masks Sometimes (NYT, 2020)	2809	0.088	0.049	0.001	0.051	0.11	0.42
Survey: Masks Frequently (NYT, 2020)	2809	0.18	0.054	0.049	0.14	0.21	0.41
Survey: Masks Always (NYT, 2020)	2809	0.63	0.14	0.17	0.53	0.76	0.88
Democrat Representative (Morris, 2020)	2809						
... No	1354	48%					
... Yes	1455	52%					
DW-NOMINATE Dim. 1 (Morris, 2020)	2809	0.028	0.47	-0.70	-0.42	0.49	0.95
DW-NOMINATE Dim. 2 (Morris, 2020)	2809	0.045	0.33	-0.87	-0.14	0.20	0.95
Trump Vote Pct. (Morris, 2016)	2809	0.47	0.16	0.067	0.36	0.59	0.80
County Rural Pct. (Census, 2019)	2809	0.21	0.23	0.00	0.024	0.35	1.00

Observations are at the institution level. NYT = New York Times, and Morris is Morris (2020).

Table 2 shows that colleges in the sample appear to be in locations that are fairly representative of the country overall, if slightly more Republican. 52% of colleges are in areas represented by a Democrat in 2020 (54% nationally), and colleges are in congressional districts with an average Trump vote share of 47% (46% nationally). There is, of course, wide variation in the Trump vote share as well as congressional DW-NOMINATE scores across the districts where colleges reside.

Mask-wearing is widely practiced, or at least people self-report wearing masks. 81% of respondents to the survey on mask-wearing reported wearing masks Frequently or Always.

COVID-19 prevalance is highly skewed, with maximum values many times the 75th percentile for cumulative cases in both March and July, and for cumulative deaths in July.

III. METHODS

III.i. LINKING FOOT TRAFFIC DATA AND CALCULATING GROWTH

In order to measure the foot traffic on individual college campuses, it is necessary to determine which locations in the SafeGraph database are a part of which campuses.

The SafeGraph Core locations have names in the data. In some cases the name includes the name of the college or university in the data they are associated with, for example the location "Fort Scott Community College." In other cases it is not clear, such as "University Tutors." So instead of attempting to match locations to institutions by name, locations are matched to the college or university that is geographically closest (and no further away than 10 miles), using the latitude and longitude of the institution as listed in IPEDS. Among locations without a match, I then check for exact matches or subset-matches ("Wayland Baptist University" is a subset of "Wayland Baptist University San Antonio Campus").

1,898 of the original 18,293 locations have no nearby match among IPEDS-listed institutions and do not have a match by name. Along with dropping locations that did not appear in both 2019 and 2020, as described in Section II.i, this drops the number of locations to 15,374.

Inspection of the mismatches shows that named locations in the SafeGraph data without an IPEDS match are generally associated with educational institutions or colleges that are for-profit or not in IPEDS, or are associated with a campus, but are so far removed from campus geographically that it seems reasonable to omit them from a measurement of campus activity. An example of the latter is campus-affiliated observatories.

With the raw count of visits to each campus in hand, I normalize the number of visits by dividing the number of visits by the total number of devices in the SafeGraph sample, which changes over time.

Foot traffic at associated locations is compared at four particular time periods: April 2019, April 2020, just after Fall opening 2019, and just after Fall opening 2020.

April foot traffic can be calculated in a straightforward way—for each institution, I add up the number of visits to associated SafeGraph locations throughout the months of April 2019 or 2020, respectively, and normalize them.

For Fall foot traffic, I aim to capture traffic in the two weeks immediately following the date that the campus opens. Pinpointing this date is not straightforward, as some colleges changed the date on which the term starts for 2020, and published term-start dates gloss over heavy pre-term foot traffic like orientation or dorm move-in dates.

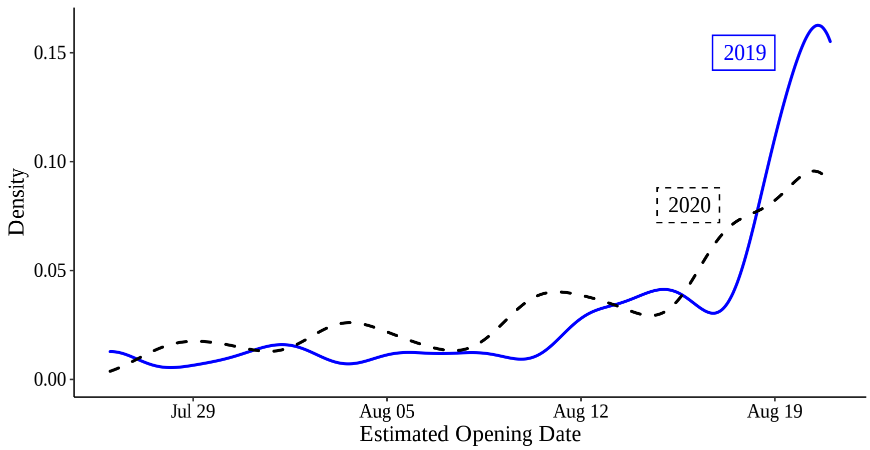
To estimate a Fall opening date for each college in each year, I take the normalized foot traffic data for weekdays only from July 15th to September 13 (the most recent date available in the 2020 data when data collection for this study stopped, late enough to capture most college opening dates).[5] Then, I split the data into before and after using each date that has ten weekdays both before and after that date, regress foot traffic on a before/after indicator, and choose the split for which the sum of squared residuals is smallest.[6]

Figure 2 shows the distribution of estimated Fall opening dates in 2019 and 2020. The weight of both the 2019 and 2020 distributions are concentrated near the end of the sample window, which makes sense given the aggregate jump in foot traffic near the end of August

[5]The use of weekdays only helps to focus analysis on the use of college campuses for academic activities.

[6]For institutions with no students on campus in Fall 2020 or a very small number, this estimate will be based on changing patterns of staff, faculty, and others visiting campus, rather than students. If staff and faculty return to campus in larger numbers as the term starts, this is still likely to pick a point near the opening date. Also, in these cases it does not matter much which break date is chosen, as the amount of foot traffic should on average not change much over the time window.

Figure 2: Distribution of Estimated Fall Opening Dates, 2019 and 2020



(a) For each college in each year, break date is estimated by splitting the sample for each weekday from July 15 to September 6 with ten days before and after in that window, and selecting the break date for which foot traffic regressed on a before/after indicator produces the smallest sum of squared residuals. Weekends appear with nonzero density here only because of smoothing.

and beginning of September, although some institutions open earlier. There is more density before that time period in 2020 than in 2019, in accordance with some institutions moving their start dates earlier so as to be able to close after Thanksgiving break.

With the estimated opening date in hand, I calculate Fall visits by adding up the visits to associated locations in the ten weekdays following (and including) the estimated opening date. Growth from fall to fall and from April to April are then calculated as a simple percentage change.[7]

Table 3 shows summary statistics for foot traffic data. The number of raw visits shows that the average college is seeing enough visits to be able to reasonably estimate a change in the number of visits. The college with the fewest recorded visits in 2019, after dropping those below the 5th percentile, is 50, but by the 25th percentile there are more than 500 recorded visits per college over the ten-weekday window. The largest campuses have tens of thousands of recorded visits over the ten-weekday window.

Statistics for foot traffic growth are shown in Table 3. There are several implausible values

[7] The use of a midpoint formula percentage change, i.e. $(New - Old)/((New + Old)/2)$, could alleviate some extremely large changes from low base rates mentioned elsewhere. However, in practice in this case, the midpoint formula does not actually eliminate unrealistic percentage changes, it just makes them unrealistic percentage changes with smaller numeric labels, and is more difficult to interpret.

Table 3: Foot Traffic Data

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Foot Traffic							
Raw Fall 2019 Visits (2019)	2809	3487.32	7269.26	50.00	585.00	3777.00	144209.00
Raw Fall 2020 Visits (2020)	2809	1650.00	3728.90	1.00	232.00	1752.00	81360.00
Normed Fall 2019 Visits*mil (2019)	2809	5.47	11.39	0.083	0.93	5.91	226.57
Normed Fall 2020 Visits*mil (2020)	2809	3.12	6.97	0.0018	0.44	3.33	149.80
Fall-to-fall Visit Growth (2020)	2809	-0.34	0.41	-1.00	-0.68	-0.061	0.73
April-to-April Visit Growth (2020)	2808	-0.76	0.21	-1.00	-0.90	-0.71	1.59

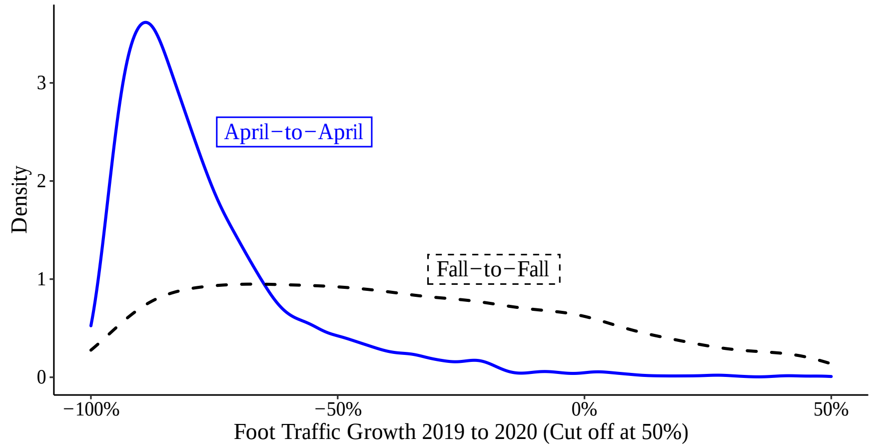
Normed visits*mil is the percentage of all national SafeGraph visits that are to that college,multiplied by 1,000,000. Data from SafeGraph. Locations linked to colleges as described in Section III.i. Restricted sample is used in which the colleges below the 5th percentile of Fall 2019 visits are dropped, as are the colleges above the 90th percentile of Fall-to-Fall growth.

for growth, even after dropping those with Fall growth above the 90th percentile or Fall 2019 visits below the 5th percentile. It is highly unlikely, for example, that any institution saw a 159% increase in foot traffic from April 2019 to April 2020. A 73% increase from Fall 2019 to Fall 2020 is possible but also unlikely. A complete drop to 0 foot traffic on any campus is also unlikely, as implied by a -100% growth rate, and instead represents a very large decline at a combined with sampling variation that happens to pick up no visits.

However, the inner ranges of growth are reasonable, with the 25th and 75th percentiles of April growth from -90% to -71%, and for Fall growth from -68% to -6%. This implies that some colleges did not get matched effectively to representative SafeGraph locations, or noisy growth estimates from small institutions. Analysis will use both the reported sample as well as a subsample that aggressively omits the top tail of the growth distribution.

The density distribution of foot traffic growth is in Figure 3. In this graph we see much less variation across colleges in their response to COVID-19 in April, where nearly all colleges saw a 50% drop in foot traffic or more. The distribution for Fall-to-Fall change is much wider, illustrating the much wider range of responses to Fall reopenings. Notable in the Fall-to-Fall distribution is the lack of any bunching—the distribution is nearly uniform. This indicates that categorial reopening measures like “fully open” and “partially open” contains policies

Figure 3: Distribution of Foot Traffic Growth from 2019 to 2020



(a) "Fall" defined and growth calculated as in Section III.i. The x-axis is cut off at 50% positive growth, which omits five observations not already excluded from the April-to-April distribution, and 97 from Fall-to-Fall.

that vary widely in terms of how much they actually reduce foot traffic on campus.

III.ii. ANALYSIS

The goal of this paper is to provide descriptive evidence of which college, student, or political attributes were predictive of lighter or stronger campus shutdowns.[8]

For a given measure of growth, I first examine the relationship between growth and each college attribute separately for two- and four-year institutions. While all attributes are evaluated at least in the appendix, there are several attributes of particular interest because they would be expected to contribute to a reopening decision during a pandemic: tuition revenue share, dormitory capacity, private status, online experience, county disease prevalence, and all political environment variables.

Then I perform several linear multivariate analyses. These serve two purposes. First, I evaluate the proportion of variation in foot traffic growth that is linearly explained by attributes overall or by different groups of variables—all political variables for example.

[8] I do not attempt to identify any causal effects. If a reader wishes to interpret the results of this paper causally, they must be willing to assume that trends in foot traffic in the absence of the pandemic would be unrelated to the "treatment" attribute of interest, which may be a strong claim.

Second, for select variables that may be of particular interest—tuition revenue share, dormitory capacity, online experience, and certain political variables—I can determine whether any apparent association can be explained by the relationship between those variables and covariates like student characteristics or how rural the area is.

Foot traffic growth is measured in several ways. The primary analysis uses fall-to-fall foot traffic growth measured as described in Section III.i. I expand analysis in two different ways. First, I see whether results are being driven by colleges for which foot traffic growth measures appear to be erroneous. I repeat some of the main analyses but narrow the sample further by changing how extreme values are treated.

Second, I use April-to-April growth. There is considerably less variation in April-to-April growth than in Fall-to-Fall growth—the standard deviation is about half as large. April-to-April analysis allows me to show whether the predictors of reopening (or staying open) differ in April and in Fall, a representation of the rapid way in which policy considerations of COVID-19 shifted throughout the year.

In all linear analyses, variables with a large amount of skew—FTE enrollment, dormitory capacity per FTE, and COVID-19 cases and deaths—are transformed using an inverse hyperbolic sine transform. The inverse hyperbolic sine transform has similar properties to the logarithm and can be interpreted in a similar percentage-change manner for large values, but also accepts a value of zero, which it maps to zero (Pence, 2006). A value of zero is common in dormitory capacity and in COVID-19 cases and deaths. The inverse hyperbolic sine transform has seen widespread usage in application to other skewed nonnegative variables for which zero is common (e.g., Card and DellaVigna, 2020; Bellemare and Wichman, 2020).

III.iii. SPATIAL AUTOCORRELATION

This study is fundamentally spatial—the dependent variable is based on visit counts to nearby affiliated locations, and many of the predictive variables are based on county population preferences or values. Clustering at a certain geographic level, such as county, would not be sufficient, as counties with similar values are likely to be near each other.

As such, any regression model's errors would not be independent, and would be correlated spatially.[9] Ignorance of spatial correlation can lead to overconfidence in predictive power and amplify the effect of variables with weak or no relationship with the dependent variable in any spatial context, not just for colleges (Ploton et al., 2020).

To account for this, for all linear regression results I estimate a spatial autocorrelation model using maximum likelihood (Ord, 1975; Darmofal, 2015). The effective equation is

$$Growth_i = \rho W \times Growth + \beta X_i + \varepsilon \tag{1}$$

Where $Growth_i$ is the foot traffic growth for college i, X_i is a set of predictor variables, ε is an error term, W is a matrix of "neighbor-weights," selected using a nearest-neighbor search for the five nearest college neighbors, and $Growth$ is the set of growth values from all observations. ρ is the spatial autocorrelation parameter. Estimation of ρ proceeds by maximum likelihood (Bivand and Piras, 2015).

In the estimated model, each variable X_i then has both a direct effect β and an indirect effect through spillovers via ρ. In discussion of the results, I will calculate and discuss these direct effects. However, a reader interpreting a regression coefficient in a table as a linear direct relationship will never be far off.

IV. RESULTS

Linear regression results are shown for different groups of variables in Tables 4-7. "Kitchen sink" regressions with all variables are available in Table A.11, but these give only a general sense of which relationships can be explained with other covariates, and because of collinearity and difficulty of interpretation are not meant to be taken as main results. In most cases,

[9]While not shown, models in this paper estimated using OLS routinely have statistically significant Moran I statistics.

results in the main table and in Table A.11 are similar.

Table 4 looks at institutional measures as predictorsn for both two- and four-year institutions.

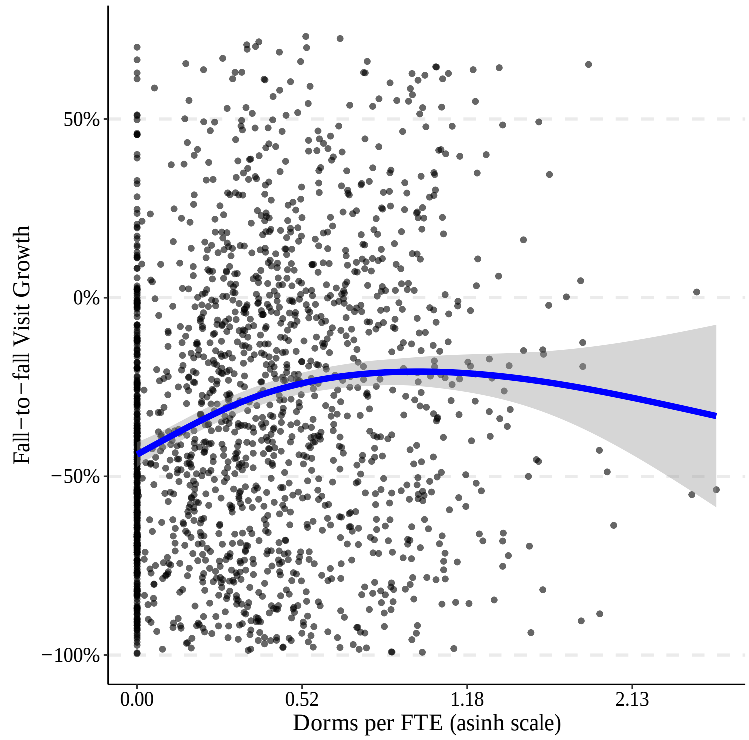
Table 4: Predicting Fall-to-Fall Growth with Institutional Data

Two-Year Institutions	Dormitories	Private	Online Share	Tuition Share	Institution
Offers Dormitories	0.131 ***				0.163 ***
	(0.039)				(0.039)
Dorms per FTE (asinh)	0.087				0.005
	(0.097)				(0.097)
Private Non-profit		0.076 **			-0.052
		(0.037)			(0.041)
Pct. Studs Exclusively Online			-0.043		0.190 *
			(0.103)		(0.104)
Pct. Studs Somewhat Online			0.044		0.212 ***
			(0.079)		(0.080)
Tuition Revenue Share				0.036	
				(0.054)	
Multi-Inst. Org.					-0.037
					(0.023)
Fall FTE (asinh)					-0.067 ***
					(0.008)
ρ	0.414 ***	0.442 ***	0.437 ***	0.402 ***	0.372 ***
	(0.038)	(0.037)	(0.037)	(0.049)	(0.038)
Intercept	-0.252 ***	-0.223 ***	-0.219 ***	-0.249 ***	0.205 ***
	(0.020)	(0.019)	(0.023)	(0.030)	(0.060)
N	1062	1066	1063	644	1062
Log Likelihood	-490.346	-501.964	-502.542	-284.768	-452.618
R^2	0.164	0.158	0.155	0.131	0.211

Four-Year Institutions	Tuition Share	Dormitories	Online Share	Private	Institution
Offers Dormitories	0.078 ***				0.117 ***
	(0.028)				(0.034)
Dorms per FTE (asinh)	0.131 ***				0.106 **
	(0.035)				(0.042)
Private Non-profit		0.073 ***			0.026
		(0.019)			(0.028)
Pct. Studs Exclusively Online			0.077		0.173 ***
			(0.055)		(0.056)
Pct. Studs Somewhat Online			-0.090 *		0.010
			(0.053)		(0.056)
Tuition Revenue Share				0.002	
				(0.037)	
Multi-Inst. Org.					0.001
					(0.026)
Fall FTE (asinh)					-0.012
					(0.008)
ρ	0.329 ***	0.358 ***	0.349 ***	0.355 ***	0.324 ***
	(0.032)	(0.031)	(0.031)	(0.032)	(0.032)
Intercept	-0.312 ***	-0.240 ***	-0.190 ***	-0.191 ***	-0.277 ***
	(0.022)	(0.018)	(0.017)	(0.022)	(0.075)
N	1734	1743	1734	1652	1734
Log Likelihood	-807.073	-830.804	-831.674	-790.005	-798.176
R^2	0.111	0.099	0.093	0.094	0.119

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Figure 4: Fall-to-fall Foot Traffic Growth and Dormitories per FTE at Four-year Institutions



(a) LOESS fit shown with 95% confidence interval for the local mean. Omitted four outliers with very large numbers of dormitories per FTE.

For both two- and four-year institutions, colleges that offer dormitories had much smaller declines than those without dormitories. Among four-year institutions, the number of available dorms relative to FTE was also a strong predictor of less foot traffic decline, with a direct association between a 10 percentage point (pp) increase in dorms and a 1.33pp increase in foot traffic growth, controlling for whether dorms are offered at all.[10] This is still fairly small relative to the variation in the data, as demonstrated by LOESS fit in Figure 4, which also shows that the relationship between dormitories per FTE and foot traffic growth levels out at around .5 dormitories per FTE.

Private colleges shut down much less than public colleges, for both two- and four-year institutions, with a direct relationship of .078pp for two-year colleges and .075pp for four-

[10] The "direct effect" here, as calculated from the spatial model discussed in Section III.iii, is similar to an average marginal effect from a logit or probit model, accounting for effects at different parts of the distribution and how they interact with spillovers, which is why it does not match the coefficient.

year colleges. However, both effects shrink in the presence of other controls, in particular Fall FTE. Private colleges saw smaller declines, but this appears to be related to the other institutional attributes that private colleges share.

The next two columns contain surprising results. Relative to the proportion of students who are fully face-to-face, there is no meaningful relationship between colleges having students partially or fully online in 2018 and shutting down more fully in 2020. We might have expected that colleges with more experience in online education may have been more willing to transition more readily online and shut down more fully, but this appears to not be the case. In fact, in the presence of other controls in the final column, some of these effects are positive, implying that schools with more online education in 2018 had smaller foot traffic declines. However, these effects are meaningfully small and generally insignificant.

Perhaps also surprising is the lack of any relationship between tuition revenue share and shutdown. We might have expected schools more reliant on tuition dollars, and worried about losing those funds if students preferred to skip an online year, to be more likely to open fully. But this does not appear to be the case. This analysis may be impacted by the fact that tuition revenue share was missing for a large portion of the sample, especially for two-year institutions, which is why it is not included in the final column.

Table 5 predicts Fall-to-Fall growth patterns using student information. We can first see that, among four-year institutions, colleges with a higher proportion of undergraduates had larger reopenings. However, this relationship shrinks and reverses sign in the presence of other controls.

A much stronger relationship, however, is that for both two- and four-year colleges, the proportion of students who are non-white was related very strongly to bigger declines in foot traffic, especially the proportion of students who are Asian. There is a direct relationship between a 10pp increase in the proportion of a two-year institution that is Asian and a -11.2pp decrease in foot traffic growth.

The racial effect has a consistent sign, and is consistently large, across all non-white

Table 5: Predicting Fall-to-Fall Growth with Student Data

Two-Year Institutions

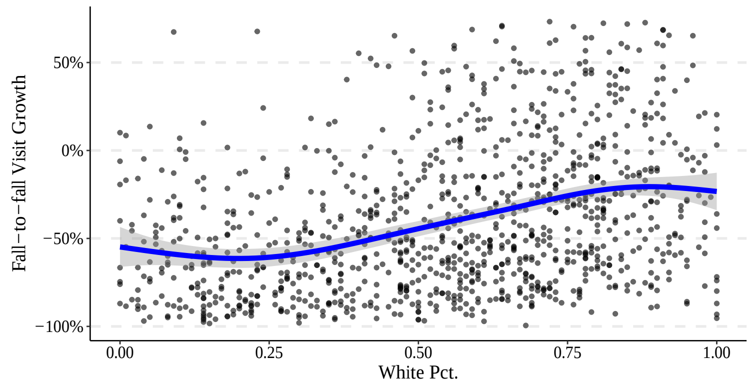
	Race	Non-local	Students
Asian Pct.	-1.135 ***		-1.000 ***
	(0.216)		(0.230)
Black Pct.	-0.283 ***		-0.253 ***
	(0.069)		(0.069)
Hispanic/Latino Pct.	-0.388 ***		-0.354 ***
	(0.062)		(0.062)
ANPI/Other/Multi race Pct.	-0.235 **		-0.245 **
	(0.112)		(0.111)
Out-of-State Pct.		0.609 ***	0.456 ***
		(0.121)	(0.121)
Foreign Pct.		-1.951 ***	-0.987 **
		(0.441)	(0.467)
Women Pct.			-0.155 **
			(0.073)
ρ	0.304 ***	0.428 ***	0.319 ***
	(0.041)	(0.037)	(0.040)
Intercept	-0.103 ***	-0.229 ***	-0.031
	(0.025)	(0.019)	(0.051)
N	1063	1038	1038
Log Likelihood	-461.237	-465.110	-432.602
R^2	0.190	0.189	0.220

Four-Year Institutions

	Undergrads	Race	Non-local	Students
Undergrad Pct.	0.095 ***			-0.059
	(0.031)			(0.059)
Asian Pct.		-0.836 ***		-1.069 ***
		(0.132)		(0.182)
Black Pct.		-0.322 ***		-0.338 ***
		(0.051)		(0.055)
Hispanic/Latino Pct.		-0.579 ***		-0.576 ***
		(0.074)		(0.082)
ANPI/Other/Multi race Pct.		-0.204 **		-0.251 **
		(0.102)		(0.109)
Out-of-State Pct.			0.156 ***	0.045
			(0.044)	(0.045)
Foreign Pct.			-0.083	-0.107
			(0.163)	(0.165)
Women Pct.				-0.039
				(0.070)
ρ	0.340 ***	0.254 ***	0.369 ***	0.260 ***
	(0.032)	(0.033)	(0.033)	(0.035)
Intercept	-0.270 ***	-0.058 ***	-0.217 ***	0.035
	(0.027)	(0.021)	(0.018)	(0.074)
N	1734	1734	1509	1509
Log Likelihood	-829.161	-775.558	-732.596	-680.011
R^2	0.093	0.133	0.112	0.153

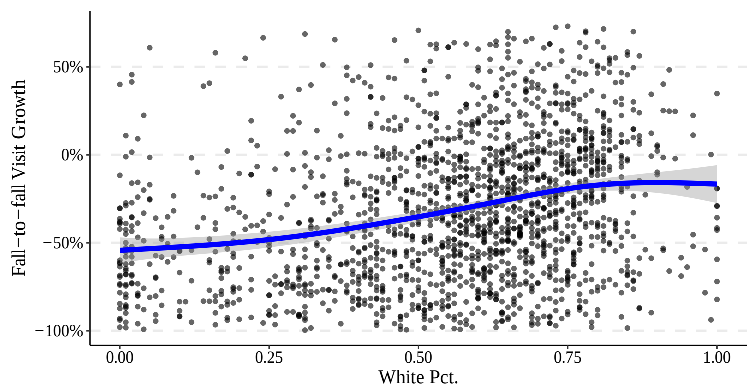
*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Figure 5: Fall-to-fall Foot Traffic Growth and Proportion White at Two-year Institutions



(a) LOESS fit shown with 95% confidence interval for the local mean.

Figure 6: Fall-to-fall Foot Traffic Growth and Proportion White at Four-year Institutions



(a) LOESS fit shown with 95% confidence interval for the local mean.

races and ethnicities. This effect is summed up in Figures 5 and 6, which show LOESS-fit local means. In both cases we see a flattened S-shaped relationship, with average foot traffic growth around -50% for colleges that are less than 25% white, around -25% for colleges that are more than 75% white, and with a gradual shift from one to the other in the middle. The effect persists when other student controls are added. In Appendix Table A.11 when all controls are added, the coefficients maintain their sign and are still large, but they do shrink, and many lose significance. Some of the racial relationship has to do with the institutions or geographic locations that white students select.

Because of differences in the ways that colleges anticipate out-of-state and foreign students to respond to campus reopenings, we might expect that colleges tailor their reopening plans based on the proportion of students who are non-local. There is not much relationship between foreign students and foot traffic growth—the effect for four-year colleges is small, and while the coefficient is very large for two-year colleges, there is so little variation in the variable (the 75th percentile is 1%) that the effect is meaningfully of little importance. For the percentage of out-of-state students, the coefficient is large, positive, and significant for both two- and four-year institutions, but for two-year institutions, this is again based on very little variation (the 75th percentile is 3%), and for four-year institutions, the effect is lost with the addition of other controls. Four-year institutions with more out-of-state students did open up considerably more, but this can be explained by the kinds of students that attend institutions with more out-of-state students.

The responsiveness of college reopenings to disease prevalence is shown in Table 6. The coefficients here are all negative, showing that colleges in areas with higher COVID prevalence did have smaller reopenings in Fall 2020, as might be expected. The effects are also meaningfully large. There is a direct relationship between a 1pp increase in the July population infection rate and a 3.31pp decrease in foot traffic growth for two-year colleges, or 3.56pp for four-year colleges. An increase in the population fatality rate of .1pp would be considered large, and relates to a 7.82pp reduction in growth for two-year institutions, or a 6.03pp reduction for four-year institutions.

The large negative relationships in Table 6 mask some potentially unexpected nonlinearities. One might expect that colleges respond especially harshly to unusually high case or death rates. However, the negative effects in Table 6 appear to be cases where colleges in areas that are almost entirely unaffected are more likely to reopen strongly, but these drop off quickly as any meaningful amount of prevalence appears, before leveling off. This is shown in Figures 7 and 8, and the relationship is similar for all six relationships in Table 6.

Finally, the relationship between foot traffic growth and political variables is shown in Table 7.

The first two columns for both two-year and four-year colleges indicate that colleges in

Table 6: Predicting Fall-to-Fall Growth with COVID-19 Data

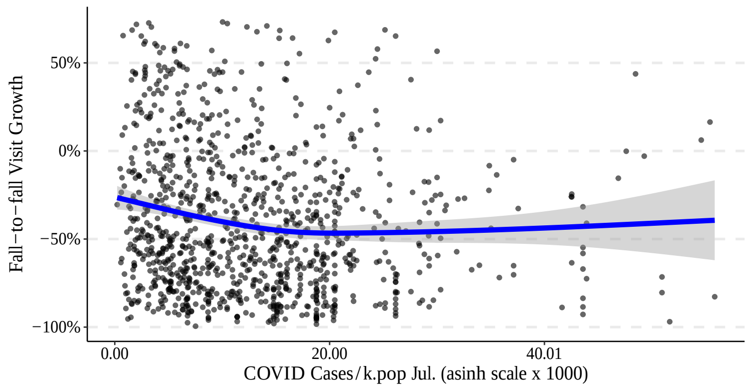
	Two-Year Institutions	Four-Year Institutions
Cases/k.pop Mar. 31 (asinh)	-18.565	-24.330 ***
	(12.669)	(8.540)
ρ	0.428 ***	0.308 ***
	(0.038)	(0.033)
Intercept	-0.227 ***	-0.205 ***
	(0.020)	(0.014)
Log Likelihood	-435.438	-797.720
R^2	0.148	0.075

	Two-Year Institutions	Four-Year Institutions
Cases/k.pop Jul. 31 (asinh)	-3.191 **	-3.487 ***
	(1.271)	(1.080)
ρ	0.426 ***	0.335 ***
	(0.037)	(0.032)
Intercept	-0.180 ***	-0.155 ***
	(0.024)	(0.019)
Log Likelihood	-500.899	-832.735
R^2	0.154	0.091

	Two-Year Institutions	Four-Year Institutions
Deaths/k.pop Jul. 31 (asinh)	-75.510 ***	-59.192 ***
	(26.653)	(19.692)
ρ	0.425 ***	0.334 ***
	(0.037)	(0.032)
Intercept	-0.193 ***	-0.176 ***
	(0.020)	(0.015)
N	1066	1743
Log Likelihood	-500.001	-833.441
R^2	0.155	0.090

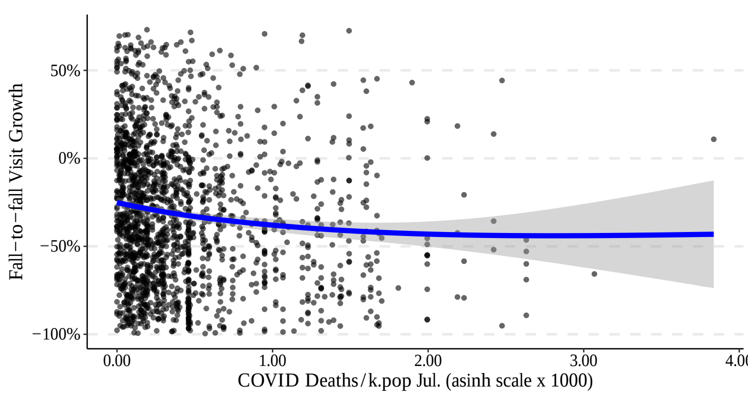
*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Figure 7: Fall-to-fall Foot Traffic Growth and Cumulative COVID-19 Cases in County by July 31, 2020 at Two-year Institutions



(a) LOESS fit shown with 95% confidence interval for the local mean.

Figure 8: Fall-to-fall Foot Traffic Growth and Cumulative COVID-19 Deaths in County by July 31, 2020 at Four-year Institutions



(a) LOESS fit shown with 95% confidence interval for the local mean.

Table 7: Predicting Fall-to-Fall Growth with Political Data

Two-Year Institutions

	Trump	DW-NOMINATE	Mask Survey	Politics
Trump Vote Pct.	0.550 ***			-0.145
	(0.075)			(0.118)
DW-NOMINATE Dim. 1		0.169 ***		0.047
		(0.026)		(0.083)
DW-NOMINATE Dim. 2		0.197 ***		0.129 ***
		(0.035)		(0.035)
Survey: Masks Rarely			0.521	0.377
			(0.549)	(0.545)
Survey: Masks Sometimes			-0.182	-0.224
			(0.482)	(0.477)
Survey: Masks Frequently			0.068	0.191
			(0.394)	(0.393)
Survey: Masks Always			-1.070 ***	-0.903 ***
			(0.328)	(0.334)
Democrat Representative				0.013
				(0.073)
County Rural Pct.				0.174 ***
				(0.052)
ρ	0.343 ***	0.312 ***	0.168 ***	0.143 ***
	(0.040)	(0.040)	(0.044)	(0.044)
Intercept	-0.525 ***	-0.294 ***	0.313	0.195
	(0.046)	(0.021)	(0.326)	(0.343)
N	1066	1066	1066	1066
Log Likelihood	-479.128	-463.604	-415.222	-401.121
R^2	0.169	0.189	0.249	0.268

Four-Year Institutions

	Trump	DW-NOMINATE	Mask Survey	Politics
Trump Vote Pct.	0.508 ***			0.229 **
	(0.058)			(0.092)
DW-NOMINATE Dim. 1		0.137 ***		0.064
		(0.021)		(0.070)
DW-NOMINATE Dim. 2		0.078 ***		0.031
		(0.029)		(0.030)
Survey: Masks Rarely			-0.062	0.021
			(0.561)	(0.559)
Survey: Masks Sometimes			0.257	0.469
			(0.458)	(0.457)
Survey: Masks Frequently			0.040	0.361
			(0.404)	(0.406)
Survey: Masks Always			-0.788 **	-0.420
			(0.335)	(0.343)
Democrat Representative				0.091
				(0.063)
County Rural Pct.				0.151 ***
				(0.052)
ρ	0.254 ***	0.281 ***	0.182 ***	0.148 ***
	(0.034)	(0.033)	(0.036)	(0.036)
Intercept	-0.460 ***	-0.221 ***	0.230	-0.282
	(0.033)	(0.014)	(0.336)	(0.349)
N	1743	1743	1743	1743
Log Likelihood	-801.542	-807.849	-769.953	-757.071
R^2	0.110	0.107	0.137	0.148

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

areas further to the political right had much smaller Fall-to-fall foot traffic declines. This shows up when political environment is measured by the 2016 Trump vote percentage, where a 1pp increase in the Trump vote percentage relates to about a .5pp increase in foot traffic growth for both two- and four-year institutions. This result also shows up when measuring the conservatism of the local congressional representative using DW-NOMINATE, on either the economic or social dimensions.

It is important at this point to recall that these results are descriptive and non-causal. We have here the result that more-conservative areas had bigger Fall reopenings. However, it is difficult to disentangle the relationships between the different measures of political conservatism, the rural/urban divide, and foot traffic growth, given the strong correlations between them, as high as .78 between Trump Vote Pct. and DW-NOMINATE Dim 1., and no lower than .25 (between County Rural Pct. and Dim 2).[11] For both two- and four-year colleges, only one of the political variables retains its effect in the final column with all political controls included. Similarly most effects are lost in the "kitchen sink" model in Appendix Table A.11. In both cases this is variance inflation—the effects on the Trump and NOMINATE variables change with the addition of the other, and with rural percentage.[12]

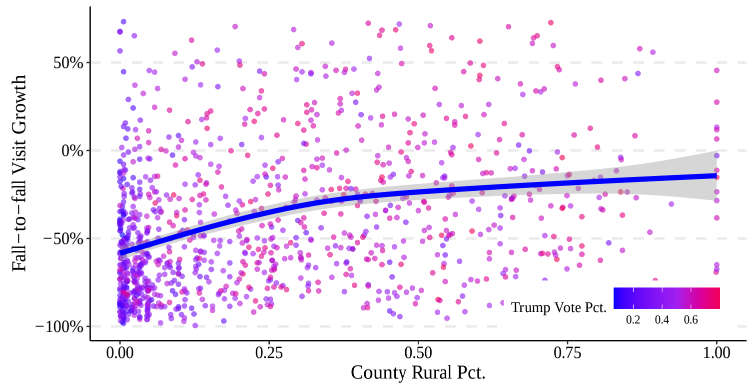
This collinearity is demonstrated in Figure 9, where there is a cluster of blue (low Trump vote percentage) points to the far left on the graph and fairly low in terms of foot traffic growth. Points to the northeast of this cluster are both more rural and had stronger openings, but also shift from blue to purple and red (more Trump).

A more direct measure of political environment as it relates to COVID-19 specifically is in the third column. These are self-report survey responses about mask-wearing, and are likely to be more reflective of beliefs about the importance of masks and the threat of COVID-19 than actual mask-wearing prevalence. Here, the proportion of respondents in the

[11]The correlation between DW-NOMINATE Dim 1 and Dim 2 is a bit lower at .22, but these are designed to capture different measurements.

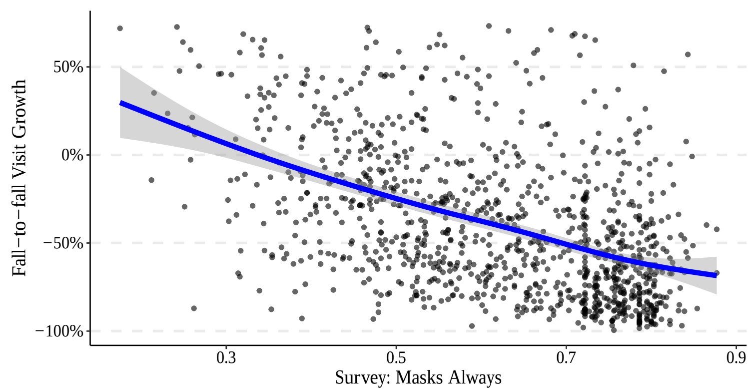
[12]The political results are unrelated to the racial results from Table 5. The correlation between the percentage of a college's students that are white and any of the political or rural percentage variables mentioned here is never higher than .05 in absolute value.

Figure 9: Fall-to-fall Foot Traffic Growth, County Rural Pct., and Trump Vote Pct. at Two-year Institutions



(a) LOESS fit shown with 95% confidence interval for the local mean.

Figure 10: Fall-to-fall Foot Traffic Growth at Two-year Institutions and Share Reporting they Always Wear Masks

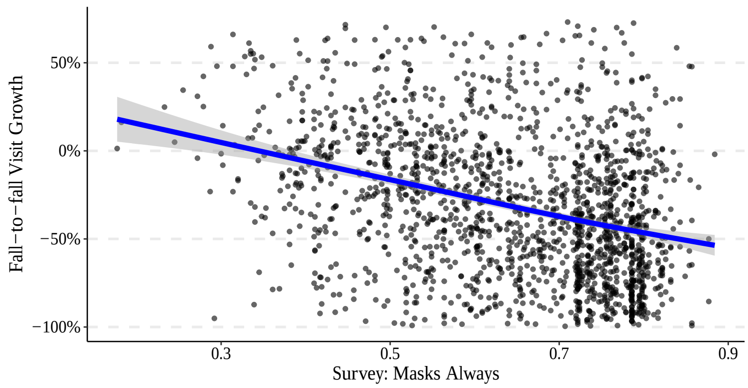


(a) LOESS fit shown with 95% confidence interval for the local mean.

county that report never wearing a mask is the reference group. There does not appear to be any difference in reopening foot traffic growth in comparing the proportion who rarely, sometimes, or frequently wear a mask to the proportion who never do. In analyzing these results it is important to keep in mind that the "Always" category is both the largest (mean .63) and has the most variation (standard deviation of .14), as shown in Table 2. Looking at the "Always" category alone may be instructive. As shown in Figures 10 and 11, the local mean of foot traffic growth changes significantly for both institution types over the range of share reporting they always wear masks, and in an apparently linear fashion.

Taking these results in total, we can characterize colleges with larger Fall 2020 reopenings

Figure 11: Fall-to-fall Foot Traffic Growth at Four-year Institutions and Share Reporting they Always Wear Masks



(a) LOESS fit shown with 95% confidence interval for the local mean.

as having more dormitories (for four-years), more likely to be private, having whiter student bodies, more out-of-state students, and being in areas that are more rural, politically more conservative, and have a smaller share of respondents who report always wearing a mask.

While these relationships do appear in the data, none of them explain an overwhelming proportion of the variation in foot traffic growth. The figures in this section show clear slopes on the LOESS curves demonstrating local means, but also huge amounts of variation around the curves. Much of the variation in reopening is idiosyncratic, unexplained, and random.

In all models, the spatial autocorrelation term is statistically significant at the 1% level and meaningfully large, implying both that foot traffic changes are spatially clustered and that spillover relationships are strong. Spatial clustering in fact explains more of the variation in the dependent variable than many of the predictor variables. We can take the R^2 values of .131 and .094 from the effectively-null result in Column 4 of Table 4 as a baseline of how much of the variation is explained by spatial autocorrelation for two- and four-year institutions. R^2 values in other models certainly exceed those values, as they must by construction of the R^2 statistic, but in many cases not by much.

IV.i. ALTERNATE GROWTH MEASUREMENTS

In this section, I use two different measurements of foot traffic growth and re-perform the analyses from the previous section.

First, I consider the wide range of the foot traffic growth measure. Estimates from the SafeGraph data find that quite a few colleges have increases in foot traffic from 2019 to 2020. As discussed in Section II.i, this is an overstatement—the raw level of growth will be overstated due to changes in the SafeGraph sample over time, possibly by as much as 21%, so many of these positive values are likely actual negative values. Still, there are several unrealistic growth estimates in the data, especially on the top end, which is why the main analysis omits observations below the 5th percentile of raw 2019 visits, or above the 90th percentile of growth.

To be more conservative, I rerun all analyses while omitting every positive growth estimate. To be clear, this is selecting heavily on the dependent variable, and only makes sense if we assume that these values are all incorrect rather than just high, which was the impetus behind the original sample limitation. This exercise is only to see whether the original results are being driven by observations that may simply be measurement error. Appendix Tables A.12-A.15 show the results. With a few exceptions the results are consistent with those from Section IV, although coefficients in some cases shrink towards zero and/or lose significance. Coefficients on some of the race variables for two-year institutions lose their size and/or significance, although the general distinction between white enrollment and other races and ethnicities remains. The collinearity issue for the political variables pushes the Trump Vote Pct. coefficient to be negative for two-year institutions with all political variables included. For four-year institutions, dorms per FTE (although not the indicator for having dorms at all), Undergrad Pct., Out-of-State Pct., and Masks Always lose their size and/or significance. COVID-19 prevalence predictors lose significance for two-year institutions.

While results are not entirely robust to the removal of colleges with positive growth estimates, keep in mind that these revised estimates are biased because they select heavily on the dependent variable, and the point here is not to provide corrected results robust to outliers but rather to show that estimates are not entirely driven by the colleges at the top of the growth distribution, who may or may not have positive growth given aggregate overstatement of growth.

Second, I evaluate foot traffic growth from April 2019 to April 2020, rather than the Fall. There is considerably less variation in foot traffic growth in April 2020, with barely any colleges attempting to remain anywhere near entirely open. However, even in this environment there are gradations in how much reduced traffic to campuses there actually was.[13]

For these analyses, I use the same sample restrictions as for the fall, removing colleges below the 5th percentile of April 2019 visits, and above the 90th percentile of growth, and also omit any predictors measured after April 2020, which includes July 31 COVID-19 cases and deaths, and mask survey results.

In April, the determinants of foot traffic growth are considerably different than they are in Fall. While the relationship between growth and dormitories is weaker in April, other institutional characteristics are more strongly predictive, as shown in Table 8. Private institutions had smaller foot traffic declines, and this relationship now survives the addition of other controls. The coefficient on tuition revenue share is now positive and significant for both two- and four-year institutions, although the effect is not large. Surprisingly, a higher proportion of students already taking online courses is associated with smaller foot traffic declines in April.

Effects for students and virus predictors are weaker in April. The relationship between white students and reopening is largely absent in April, as is the relationship with out-of-state students. Some colleges in April were allowing foreign students to stay on campus while other students went home, so the lack of a large relationship with foreign student percentage

[13] In some cases, additional foot traffic on campuses in April may be due to the conversion of campus property into overflow hospital beds (e.g Binkley, 2020), although it is not clear how widely this was actually used and is likely to be small.

Table 8: Predicting April-to-April Growth with Institutional Data

Two-Year Institutions					
	Dormitories	Private	Online Share	Tuition Share	Institution
Offers Dormitories	0.020 *				0.035 ***
	(0.012)				(0.012)
Dorms per FTE (asinh)	0.028				-0.020
	(0.032)				(0.032)
Private Non-profit		0.085 ***			0.074 ***
		(0.013)			(0.014)
Pct. Studs Exclusively Online			0.132 ***		0.181 ***
			(0.032)		(0.032)
Pct. Studs Somewhat Online			-0.052 **		-0.008
			(0.026)		(0.027)
Tuition Revenue Share				0.072 ***	
				(0.018)	
Multi-Inst. Org.					0.019 ***
					(0.007)
Fall FTE (asinh)					-0.012 ***
					(0.003)
ρ	0.224 ***	0.242 ***	0.225 ***	0.236 ***	0.223 ***
	(0.045)	(0.044)	(0.045)	(0.058)	(0.044)
Intercept	-0.640 ***	-0.627 ***	-0.639 ***	-0.643 ***	-0.581 ***
	(0.037)	(0.036)	(0.037)	(0.048)	(0.040)
N	1061	1065	1062	623	1061
Log Likelihood	777.412	797.236	780.814	466.080	823.229
R^2	0.042	0.072	0.048	0.060	0.120

Four-Year Institutions					
	Dormitories	Private	Online Share	Tuition Share	Institution
Offers Dormitories	-0.051 ***				-0.003
	(0.008)				(0.009)
Dorms per FTE (asinh)	0.018 *				-0.025 **
	(0.010)				(0.012)
Private Non-profit		0.034 ***			0.019 ***
		(0.005)			(0.007)
Pct. Studs Exclusively Online			0.044 ***		0.027 *
			(0.016)		(0.016)
Pct. Studs Somewhat Online			0.060 ***		0.066 ***
			(0.015)		(0.015)
Tuition Revenue Share				0.031 ***	
				(0.011)	
Multi-Inst. Org.					0.011
					(0.007)
Fall FTE (asinh)					-0.018 ***
					(0.002)
ρ	0.236 ***	0.230 ***	0.216 ***	0.231 ***	0.231 ***
	(0.035)	(0.035)	(0.035)	(0.036)	(0.034)
Intercept	-0.586 ***	-0.646 ***	-0.651 ***	-0.639 ***	-0.491 ***
	(0.028)	(0.028)	(0.029)	(0.030)	(0.034)
N	1744	1754	1744	1666	1744
Log Likelihood	1411.541	1408.402	1401.113	1329.207	1480.990
R^2	0.060	0.053	0.047	0.039	0.130

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

indicates this effect was not large. Increased virus prevalence still has a meaningful and negative relationship with foot traffic growth, but it is not strongly significant in April. These results are in Appendix Tables A.16 and A.17.

Perhaps the most interesting distinction between April and Fall is in Table 9. Unlike in Fall where there are strong relationships between political variables and foot traffic growth, these effects are either absent or greatly diminished in April. None of the political variables hold predictive power for four-year institutions. Rural percentage has a significant effect but it is small and, contrary to Fall, negative. There are some significant relationships for two-year institutions, but these effects are a tenth of their size in Fall.

IV.ii. FOLLOWING LARGE COLLEGES

In this section I look at the institutional decision-making process from another angle. A massive pandemic is, for many institutions and especially for the administrators making decisions in those institutions, a first-ever occurrence for which nobody really knows what to do. In cases of high uncertainty, there is additional incentive to mimic the choices of others. Institutions especially likely to be mimicked are high-status, central, and “alike” (nearby or in a similar sector) to a decision-making organization (Eckel et al., 2010; Marquis and Tilcsik, 2016).

In this section I follow de Vaan et al. (2020) in looking for these sorts of influences during COVID shutdowns. In their paper, they look at the impact of COVID shutdown decisions made by large national chains on the decisions of nearby local establishments in the same industry.[14] They find support for these follow-the-leader effects.

I split the sample of colleges into “large” and “small” based on their full-time equivalent enrollment, defining large colleges as those with 2018 FTEs of 10,000 or higher (285 institu-

[14] They make use of a Bartik instrument to provide a causal estimate, based on the level of exposure a local firm has to national chains. It seems unlikely that Bartik assumptions like exogenous initial shares hold in the context of colleges (Goldsmith-Pinkham et al., 2020), and so I do not repeat this part of their analysis.

Table 9: Predicting April-to-April Growth with Political Data

Two-Year Institutions

	Trump	DW-NOMINATE	Politics
Trump Vote Pct.	0.051 **		-0.052
	(0.023)		(0.039)
DW-NOMINATE Dim. 1		0.021 ***	0.051 *
		(0.008)	(0.027)
DW-NOMINATE Dim. 2		0.006	-0.001
		(0.011)	(0.011)
Democrat Representative			0.039
			(0.024)
County Rural Pct.			0.024
			(0.017)
ρ	0.214 ***	0.209 ***	0.176 ***
	(0.046)	(0.046)	(0.047)
Intercept	-0.669 ***	-0.649 ***	-0.573 ***
	(0.040)	(0.038)	(0.115)
N	1065	1065	1065
Log Likelihood	777.826	779.232	790.517
R^2	0.036	0.038	0.055

Four-Year Institutions

	Trump	DW-NOMINATE	Politics
Trump Vote Pct.	-0.003		-0.037
	(0.016)		(0.027)
DW-NOMINATE Dim. 1		0.004	0.007
		(0.006)	(0.020)
DW-NOMINATE Dim. 2		0.001	0.001
		(0.008)	(0.009)
Democrat Representative			0.000
			(0.018)
County Rural Pct.			-0.055 ***
			(0.015)
ρ	0.224 ***	0.223 ***	0.189 ***
	(0.035)	(0.035)	(0.036)
Intercept	-0.628 ***	-0.631 ***	-0.417 ***
	(0.030)	(0.029)	(0.102)
N	1754	1754	1754
Log Likelihood	1389.087	1389.381	1404.868
R^2	0.034	0.034	0.046

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

tions), and small as those with 2018 FTEs of 5,000 or lower (2,160 institutions). Then, for each small institution, I calculate the distance in miles to each of the large institutions. I limit the matches to institutions within 100 miles (which limits the set of small institutions with any matches to 2,006), and then construct a weighted mean of Fall-to-fall growth at the large institutions, using inverse distance weights. This weighted average of foot traffic growth at nearby large institutions is then used as a predictor of the small institution's foot traffic growth in Table 10.[15]

There is a strong positive relationship between foot traffic growth at nearby. There is a direct relationship between a 1pp increase in weighted large-college growth and a .25pp increase in small two-year colleges, or .17pp in small four-year colleges. These effects only somewhat diminish with the addition of institutional, environmental, and COVID prevance controls.

This is evidence that small colleges are making similar decisions to nearby large colleges. Under further assumptions, including an assumption that small-college decisions do not affect large-college decisions, we can consider this consistent with follow-the-leader behavior.

[15]The assumptions necessary to consider this a causal effect are weaker than in the main analysis but I still consider them untenable. We would have to assume that counterfactual trends in foot traffic growth are unrelated to the distance between a small college and large colleges. Some likely confounders for this relationship are accounted for by the controls in columns 2 and 3 but not all. We must also assume no reverse causality.

Table 10: Predicting Fall-to-Fall Growth at Small Institutions using Growth at Nearby Large Institutions

Two-Year Institutions			
	Large-College Effect	Institution Controls	+ Politics, Disease
Weighted Large-College Growth	0.245 ***	0.213 ***	0.193 ***
	(0.048)	(0.047)	(0.048)
Private Non-profit		0.089 **	0.099 **
		(0.044)	(0.045)
Fall FTE (asinh)		-0.014	-0.015
		(0.009)	(0.009)
County Rural Pct.		0.379 ***	0.337 ***
		(0.056)	(0.062)
Multi-Inst. Org.		-0.059 **	-0.060 **
		(0.027)	(0.027)
COVID Cases Jul. (asinh)			0.633
			(1.531)
Trump Vote Pct.			0.197 **
			(0.099)
ρ	0.328 ***	0.266 ***	0.249 ***
	(0.047)	(0.048)	(0.048)
Intercept	-0.137 ***	-0.158 **	-0.262 ***
	(0.026)	(0.075)	(0.091)
N	804	804	804
Log Likelihood	-362.961	-334.372	-332.391
R^2	0.133	0.185	0.188

Four-Year Institutions			
	Large-College Effect	Institution Controls	+ Politics, Disease
Weighted Large-College Growth	0.169 ***	0.139 ***	0.131 ***
	(0.039)	(0.039)	(0.039)
Private Non-profit		0.078 **	0.085 **
		(0.035)	(0.035)
Fall FTE (asinh)		0.024 ***	0.024 ***
		(0.009)	(0.009)
County Rural Pct.		0.370 ***	0.269 ***
		(0.052)	(0.059)
Multi-Inst. Org.		0.006	0.007
		(0.033)	(0.033)
COVID Cases Jul. (asinh)			0.043
			(1.292)
Trump Vote Pct.			0.316 ***
			(0.076)
ρ	0.360 ***	0.270 ***	0.232 ***
	(0.037)	(0.039)	(0.041)
Intercept	-0.097 ***	-0.454 ***	-0.599 ***
	(0.021)	(0.087)	(0.096)
N	1202	1202	1202
Log Likelihood	-551.001	-522.642	-514.078
R^2	0.123	0.150	0.159

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.
Sample includes only institutions with 2018 FTE below 5000. Weighted Large-College Growth is an inverse-distance weighted average of Fall-to-fall growth at colleges with 2018 FTE above 10,000 within 100 miles.

V. CONCLUSION

In the leadup to Fall 2020, colleges had to make an important, high-stakes choice about opening their campus. On one hand, there is the potential danger of exposing students, faculty, staff, and their family and friends to a dangerous disease. On the other is the possibility of losing tuition revenue, student satisfaction, local prestige, or even shutting down entirely as a result of a temporary shift online, as well as the possibility that they could find a way to bring students back to campus without extensive risk.

I find a number of variables related to the costs of benefits and reopening that are also related to the degree of reopening. While these are noncausal effects, they give a sense of how college institutions make complex and weighty decisions under high levels of uncertainty, or at least act as predictors of those decisions.

We see mixed results on the predictive power of incentives internal to the institutions. There is evidence that more-residential college campuses, with more dorms and more white students, had stronger reopenings, at least for four-year institutions. There is also evidence that institutions with more out-of-state students had stronger reopenings, although this can be explained by other student body characteristics on those campuses. On the other hand, there is little evidence that institutions especially reliant on tuition had larger reopenings, or that institutions with more experience delivering online instruction reopened more strongly.

Rather than incentives internal to the institution, reopening levels seemed to center around two things: cues from the local environment, and lots of noise and uncertainty.

Some of those local cues are very sensible, in particular COVID prevalence. Areas with near-zero levels of COVID deaths and cases as of the end of July 2020 had the smallest average year-to-year declines in foot traffic. It is also sensible that smaller institutions may take decision-making cues from nearby large institutions in the context of a highly uncertain decision, and that reopening behavior is likely to cluster geographically as institutions take cues from all sorts of local information and preferences.

Others are more difficult to justify. In particular, the political environment, both in terms of electoral outcomes and local surveys about COVID safety, is a fairly strong predictor of reopening behavior, beyond what can be explained by spatial autocorrelation or the rural/urban divide. This doesn't necessarily have to be the case, either—the influence of political environment was unimportant for closure decisions in April, but decisions fell along political lines by the Fall. This corresponds to the politicization of the virus response over the course of the year, and it is unlikely that optimal policy would assign reopenings more along political lines in Fall than it would in April.

Beyond internal or external cues, large amounts of the reopening decision remains unexplained. The distribution of reopening levels is very wide, and even strong predictors explain only a modest portion of the variance. We do not see uniformity in reopening decisions along any obvious axis.

In an unprecedented situation in which institutions had to make decisions about reopening with high levels of uncertainty, the observables best able to explain differences between colleges come in the form of local informational and political cues, and these leave much left unexplained. However well-aligned these responses may be to the situation of each individual college, this can be taken as indicative of a general lack of a structured idea of how to respond and how those responses can be tailored on an institutional level.

In the case of another such major unexpected event, it is likely that similar levels of uncertainty would lead to a similar lack of overarching structure in college responses. It may have been valuable to have centralized guidance, if not necessarily centralized decision-making, in Fall reopening plans, to the extent that centralized guidance could be considered reliable in unprecedented situations. Prior preparation in the establishment of a recognizable guidance organization could have changed the way that colleges made their decisions, and the usefulness of the external cues they relied on.

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Appendix A. Additional Results

Table A.11: Predicting Fall-to-Fall Growth with All Data

	Two-Year Institutions	Four-Year Institutions
Offers Dormitories	0.099 ***	0.075 **
	(0.039)	(0.033)
Dorms per FTE (asinh)	-0.125	0.034
	(0.092)	(0.045)
Private Non-profit	0.101 **	0.084 ***
	(0.041)	(0.029)
Pct. Studs Exclusively Online	0.189 *	0.052
	(0.104)	(0.057)
Pct. Studs Somewhat Online	0.055	-0.022
	(0.080)	(0.057)
Multi-Inst. Org.	-0.068 ***	0.011
	(0.023)	(0.026)
Fall FTE (asinh)	-0.042 ***	-0.002
	(0.009)	(0.008)
Undergrad Pct.		0.048
		(0.037)
Asian Pct.	-0.122	-0.232
	(0.221)	(0.148)
Black Pct.	-0.136 *	-0.296 ***
	(0.078)	(0.053)
Hispanic/Latino Pct.	-0.076	-0.346 ***
	(0.075)	(0.085)
ANPI/Other/Multi race Pct.	-0.162	-0.235 **
	(0.113)	(0.106)
Women Pct.	-0.244 ***	0.015
	(0.070)	(0.063)
Trump Vote Pct.	-0.259 **	0.153
	(0.122)	(0.094)
DW-NOMINATE Dim. 1	0.085	0.118
	(0.082)	(0.072)
DW-NOMINATE Dim. 2	0.099 ***	0.050
	(0.035)	(0.031)
Survey: Masks Rarely	0.625	0.199
	(0.579)	(0.597)
Survey: Masks Sometimes	0.240	0.812 *
	(0.505)	(0.485)
Survey: Masks Frequently	0.703 *	0.523
	(0.413)	(0.439)
Survey: Masks Always	-0.479	-0.124
	(0.352)	(0.372)
Democrat Representative	0.020	0.117 *
	(0.072)	(0.065)
County Rural Pct.	0.179 ***	0.061
	(0.063)	(0.061)
Cases/k.pop Mar. 31 (asinh)	13.011	-22.955 **
	(14.634)	(10.248)
Cases/k.pop Jul. 31 (asinh)	0.285	0.461
	(1.683)	(1.526)
Deaths/k.pop Jul. 31 (asinh)	48.809	27.425
	(35.038)	(27.922)
ρ	0.124 ***	0.102 ***
	(0.046)	(0.038)
Intercept	0.296	-0.573
	(0.371)	(0.387)
N	988	1667
Log Likelihood	-307.023	-676.703
R^2	0.311	0.180

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Table A.12: Predicting Fall-to-Fall Growth with Institutional Data, Growth Range Restricted Below 0

Two-Year Institutions	Dormitories	Private	Online Share	Tuition Share	Institution
Offers Dormitories	0.063 **				0.086 ***
	(0.029)				(0.029)
Dorms per FTE (asinh)	0.062				0.004
	(0.070)				(0.069)
Private Non-profit		0.070 ***			-0.020
		(0.027)			(0.030)
Pct. Studs Exclusively Online			0.010		0.159 **
			(0.076)		(0.076)
Pct. Studs Somewhat Online			-0.044		0.101 *
			(0.059)		(0.060)
Tuition Revenue Share				0.057	
				(0.039)	
Multi-Inst. Org.					-0.012
					(0.017)
Fall FTE (asinh)					-0.043 ***
					(0.006)
ρ	0.371 ***	0.381 ***	0.379 ***	0.359 ***	0.336 ***
	(0.044)	(0.043)	(0.043)	(0.056)	(0.043)
Intercept	-0.352 ***	-0.343 ***	-0.329 ***	-0.363 ***	-0.068
	(0.025)	(0.025)	(0.027)	(0.035)	(0.047)
N	876	880	877	533	876
Log Likelihood	-28.750	-30.746	-33.951	-11.607	2.604
R^2	0.116	0.115	0.110	0.101	0.168

Four-Year Institutions	Tuition Share	Dormitories	Online Share	Private	Institution
Offers Dormitories	0.039 *				0.081 ***
	(0.021)				(0.025)
Dorms per FTE (asinh)	0.030				0.011
	(0.027)				(0.032)
Private Non-profit		0.031 **			0.006
		(0.015)			(0.022)
Pct. Studs Exclusively Online			0.091 **		0.132 ***
			(0.042)		(0.043)
Pct. Studs Somewhat Online			0.027		0.058
			(0.040)		(0.042)
Tuition Revenue Share				0.038	
				(0.028)	
Multi-Inst. Org.					0.007
					(0.020)
Fall FTE (asinh)					-0.016 **
					(0.006)
ρ	0.287 ***	0.302 ***	0.290 ***	0.302 ***	0.279 ***
	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)
Intercept	-0.379 ***	-0.351 ***	-0.353 ***	-0.346 ***	-0.311 ***
	(0.023)	(0.021)	(0.021)	(0.024)	(0.060)
N	1340	1348	1340	1273	1340
Log Likelihood	-131.561	-133.863	-134.388	-124.127	-120.559
R^2	0.067	0.066	0.064	0.065	0.079

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Table A.13: Predicting Fall-to-Fall Growth with Student Data, Growth Range Restricted Below 0

Two-Year Institutions				
	(1)	Race	Non-local	Students
Asian Pct.	-0.686 ***	-0.579 ***		-0.501 ***
	(0.141)	(0.143)		(0.153)
Black Pct.		-0.063		-0.068
		(0.048)		(0.048)
Hispanic/Latino Pct.		-0.251 ***		-0.217 ***
		(0.044)		(0.044)
ANPI/Other/Multi race Pct.		-0.032		-0.026
		(0.081)		(0.080)
Out-of-State Pct.			0.425 ***	0.338 ***
			(0.093)	(0.094)
Foreign Pct.			-1.145 ***	-0.596 *
			(0.294)	(0.314)
Women Pct.				0.067
				(0.055)
ρ	0.329 ***	0.234 ***	0.371 ***	0.256 ***
	(0.045)	(0.048)	(0.043)	(0.048)
Intercept	-0.338 ***	-0.334 ***	-0.346 ***	-0.379 ***
	(0.025)	(0.029)	(0.025)	(0.045)
N	877	877	857	857
Log Likelihood	-22.719	-6.708	-13.313	7.104
R^2	0.118	0.139	0.142	0.166

Four-Year Institutions				
	Undergrads	Race	Non-local	Students
Undergrad Pct.	-0.003			-0.105 **
	(0.023)			(0.045)
Asian Pct.		-0.546 ***		-0.941 ***
		(0.098)		(0.138)
Black Pct.		-0.166 ***		-0.186 ***
		(0.038)		(0.040)
Hispanic/Latino Pct.		-0.365 ***		-0.389 ***
		(0.054)		(0.060)
ANPI/Other/Multi race Pct.		-0.145 *		-0.164 **
		(0.078)		(0.083)
Out-of-State Pct.			0.044	-0.047
			(0.034)	(0.036)
Foreign Pct.			-0.286 **	-0.272 **
			(0.126)	(0.128)
Women Pct.				0.010
				(0.054)
ρ	0.297 ***	0.216 ***	0.321 ***	0.199 ***
	(0.038)	(0.039)	(0.040)	(0.043)
Intercept	-0.332 ***	-0.262 ***	-0.322 ***	-0.139 **
	(0.026)	(0.023)	(0.022)	(0.060)
N	1340	1340	1138	1138
Log Likelihood	-137.149	-97.071	-112.956	-65.129
R^2	0.063	0.104	0.081	0.140

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Table A.14: Predicting Fall-to-Fall Growth with COVID-19 Data, Growth Range Restricted Below 0

	Two-Year Institutions	Four-Year Institutions
Cases/k.pop Mar. 31 (asinh)	-0.986	-15.255 **
	(8.592)	(6.290)
ρ	0.387 ***	0.276 ***
	(0.044)	(0.039)
Intercept	-0.335 ***	-0.340 ***
	(0.026)	(0.020)
Log Likelihood	-24.344	-125.178
R^2	0.114	0.059

	Two-Year Institutions	Four-Year Institutions
Cases/k.pop Jul. 31 (asinh)	-0.509	-2.938 ***
	(0.910)	(0.872)
ρ	0.376 ***	0.273 ***
	(0.043)	(0.038)
Intercept	-0.331 ***	-0.306 ***
	(0.028)	(0.022)
Log Likelihood	-33.992	-130.457
R^2	0.109	0.064

	Two-Year Institutions	Four-Year Institutions
Deaths/k.pop Jul. 31 (asinh)	-23.700	-47.580 ***
	(18.660)	(15.382)
ρ	0.375 ***	0.277 ***
	(0.043)	(0.038)
Intercept	-0.329 ***	-0.323 ***
	(0.026)	(0.020)
N	880	1348
Log Likelihood	-33.340	-131.298
R^2	0.109	0.064

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Table A.15: Predicting Fall-to-Fall Growth with Political Data, Growth Range Restricted Below 0

Two-Year Institutions	Trump	DW-NOMINATE	Mask Survey	Politics
Trump Vote Pct.	0.310 ***			-0.143 *
	(0.053)			(0.086)
DW-NOMINATE Dim. 1		0.110 ***		0.105 *
		(0.018)		(0.060)
DW-NOMINATE Dim. 2		0.092 ***		0.061 **
		(0.026)		(0.026)
Survey: Masks Rarely			-0.424	-0.492
			(0.443)	(0.438)
Survey: Masks Sometimes			-0.278	-0.260
			(0.385)	(0.383)
Survey: Masks Frequently			-0.147	-0.019
			(0.311)	(0.311)
Survey: Masks Always			-0.896 ***	-0.725 ***
			(0.262)	(0.267)
Democrat Representative				0.058
				(0.053)
County Rural Pct.				0.151 ***
				(0.039)
ρ	0.301 ***	0.283 ***	0.183 ***	0.161 ***
	(0.046)	(0.046)	(0.049)	(0.049)
Intercept	-0.527 ***	-0.396 ***	0.202	0.055
	(0.041)	(0.027)	(0.261)	(0.273)
N	880	880	880	880
Log Likelihood	-18.157	-8.451	20.080	32.292
R^2	0.123	0.140	0.186	0.207

Four-Year Institutions	Trump	DW-NOMINATE	Mask Survey	Politics
Trump Vote Pct.	0.313 ***			0.214 ***
	(0.045)			(0.072)
DW-NOMINATE Dim. 1		0.081 ***		-0.031
		(0.016)		(0.055)
DW-NOMINATE Dim. 2		0.051 **		0.019
		(0.024)		(0.025)
Survey: Masks Rarely			0.397	0.367
			(0.503)	(0.501)
Survey: Masks Sometimes			0.397	0.568
			(0.419)	(0.418)
Survey: Masks Frequently			0.527	0.725 **
			(0.356)	(0.358)
Survey: Masks Always			-0.115	0.131
			(0.305)	(0.311)
Democrat Representative				-0.009
				(0.051)
County Rural Pct.				0.062
				(0.043)
ρ	0.215 ***	0.235 ***	0.194 ***	0.159 ***
	(0.040)	(0.039)	(0.041)	(0.041)
Intercept	-0.512 ***	-0.361 ***	-0.449	-0.777 **
	(0.032)	(0.020)	(0.306)	(0.314)
N	1348	1348	1348	1348
Log Likelihood	-112.821	-118.603	-103.375	-93.812
R^2	0.081	0.075	0.092	0.103

*** p < 0.01, ** p < 0.05, *, p < 0.1. Model estimated using spatial autocorrelation lag.

Table A.16: Predicting April-to-April Growth with Student Data

Two-Year Institutions

	(1)	Race	Non-local	Students
Asian Pct.	-0.099	-0.096		-0.080
	(0.065)	(0.067)		(0.072)
Black Pct.		0.046 **		0.054 **
		(0.022)		(0.022)
Hispanic/Latino Pct.		0.008		0.018
		(0.020)		(0.020)
ANPI/Other/Multi race Pct.		0.046		0.039
		(0.035)		(0.035)
Out-of-State Pct.			0.163 ***	0.160 ***
			(0.037)	(0.038)
Foreign Pct.			-0.113	-0.042
			(0.146)	(0.161)
Women Pct.				0.002
				(0.023)
ρ	0.223 ***	0.219 ***	0.228 ***	0.220 ***
	(0.045)	(0.045)	(0.045)	(0.045)
Intercept	-0.632 ***	-0.648 ***	-0.639 ***	-0.659 ***
	(0.037)	(0.038)	(0.037)	(0.041)
N	1062	1062	1048	1048
Log Likelihood	773.422	776.069	778.224	782.183
R^2	0.036	0.039	0.053	0.059

Four-Year Institutions

	Undergrads	Race	Non-local	Students
Undergrad Pct.	-0.052 ***			-0.053 ***
	(0.009)			(0.016)
Asian Pct.		0.065		-0.121 **
		(0.040)		(0.053)
Black Pct.		0.048 ***		0.063 ***
		(0.015)		(0.015)
Hispanic/Latino Pct.		-0.007		0.028
		(0.021)		(0.022)
ANPI/Other/Multi race Pct.		0.062 **		0.077 ***
		(0.029)		(0.030)
Out-of-State Pct.			0.006	0.000
			(0.012)	(0.012)
Foreign Pct.			-0.030	0.009
			(0.049)	(0.051)
Women Pct.				-0.028
				(0.020)
ρ	0.229 ***	0.226 ***	0.232 ***	0.219 ***
	(0.035)	(0.035)	(0.037)	(0.037)
Intercept	-0.585 ***	-0.643 ***	-0.629 ***	-0.593 ***
	(0.029)	(0.029)	(0.031)	(0.036)
N	1744	1744	1555	1555
Log Likelihood	1404.506	1395.542	1294.807	1311.793
R^2	0.052	0.042	0.038	0.054

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.

Table A.17: Predicting April-to-April Growth with COVID-19 Data

	Two-Year Institutions	Four-Year Institutions
Cases/k.pop Mar. 31 (asinh)	-6.124	-4.207 *
	(4.655)	(2.359)
ρ	0.190 ***	0.207 ***
	(0.049)	(0.036)
Intercept	-0.665 ***	-0.641 ***
	(0.040)	(0.030)
N	981	1679
Log Likelihood	724.985	1321.054
R^2	0.026	0.031

*** $p < 0.01$, ** $p < 0.05$, *, $p < 0.1$. Model estimated using spatial autocorrelation lag.