We Want You Back: Uncovering the Effects on In-Person Instructional Operations in Fall 2020

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Received: 8 February 2021 / Accepted: 10 November 2021 / Published online: 30 November 2021
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Abstract

Postsecondary institutions' responses to COVID-19 are a topic of immediate relevance. Emergent research suggests that partisanship was more strongly linked to institutions offering in-person instruction for Fall 2020 than was COVID-19. Using data from the College Crisis Initiative and a multiple group structural equation modeling approach, we tested the relationships between our outcome of interest (in-person instruction in Fall 2020) and state and county sociopolitical features, state and county COVID-19 rates, and state revenue losses. Our full-sample model suggested that County Political Preferences had the strongest association with in-person instruction, followed by *Pandemic Severity* and *State Sociopolitical Features*. Because institutional sectors may be uniquely sensitive to these factors, we tested our models separately on 4-year public, 4-year private, and 2-year public and 2-year private institutions. *State Sociopolitical Features* were significantly related to in-person instruction for 4-year private and 2-year public institutions but were strongest for 4-year public institutions. For 4-year private and 2-year public institutions, County Political Preferences' effect sizes were 2–3 times stronger than effects from *State Sociopolitical Features*. *Pandemic Severity* was significantly, negatively related to in-person instruction for 4-year private and 2-year public institutions—similar in magnitude to *State Sociopolitical Features*. Our analysis revealed that COVID-19 played a stronger role in determining in-person instruction in Fall 2020 than initial research using less sophisticated methods suggested—and while *State Sociopolitical Features* may have played a role in the decision, 4-year private and 2-year public institutions were more sensitive to county-level preferences.

Keywords COVID-19 · In-person instruction · Politics · Dependency · Structural equation modeling

The COVID-19 pandemic put American higher education institutions in extremely challenging positions. When COVID-19 became a concern in Spring 2020, many institutions quickly pivoted from in-person to online instruction in response to this unprecedented

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public health threat. As summer progressed, institutions were balancing the severity of the pandemic, financial constraints, and sociopolitical pressures when determining whether Fall 2020 instruction should primarily be in-person. By October, 27% of institutions offered in-person instruction (The Chronicle of Higher Education, 2020). Emergent research suggests that political power structures and budget concerns were more strongly linked to offering in-person instruction than was the severity of the pandemic (Collier et al., 2020b; Felson & Adamczyk, 2021), and these associations were not unique to higher education (Corder et al., 2020; Holman et al., 2020). While choosing in-person instruction may have been necessary to satisfy budget pressures, legislators, and families, doing so came at the consequence of increasing the spread of the COVID-19. For example, the University of North Carolina at Chapel Hill's decision to offer in-person instructions, which they reversed within ten days, was linked to multiple clusters of outbreaks and the infection of over 1200 students and employees by September 2020 (Marris, 2020). Institutions offering in-person instruction in October were tied to 136,838 cases by December (The New York Times, 2020b)—although this number is likely an underestimate (Andersen et al., 2021). Though evidence at the time of these institutions' decisions and our writing indicated that traditional-aged students are unlikely to die from (Fall 2020 strains of) COVID-19, which was likely a factor in the decision to offer in-person instruction (Lederman, 2020), there has been evidence of adverse effects on students, staff, and communities. Even among students with mild initial cases, long-term health effects (e.g., diminished lung capacity) have emerged (Singh, 2021). Institutions offering in-person instruction resulted in at least 90 staff and faculty deaths in Fall and Winter 2020 (The New York Times, 2020b). The choice to engage in-person instruction during the Fall semester was also associated with increased COVID-19 incidence in the local area (Andersen et al., 2021). This spread from campuses to their co-located communities placed vulnerable populations (e.g., those in nursing homes) at risk; genetic sequencing confirms that campus infections preceded off-campus fatalities (Richmond et al., 2020).

Given that public trust in higher education has been eroding (Doherty et al., 2017); recovering trust may be more difficult if research confirms that higher education played a role in the spread of COVID-19. In light of the health-related ramifications of in-person instruction and the descriptive findings that suggest a weak association between pandemic severity and instructional modality, research using more rigorous quantitative methods remains critical. It is also important to examine whether different sectors of higher education, such as community colleges, public universities, and private nonprofit institutions, responded differently given their unique financial and governance structures. Leaning on the theoretical underpinning of political polarization (Iyengar et al., 2012, 2019) and resource dependency (Fowles, 2014), this exploratory study tested prior initial findings (Collier et al., 2020b) using structural equation modeling (SEM) to examine the relationships between the outcome of in-person instruction in Fall 2020 and state and county sociopolitical features, state revenue declines, and state and county COVID-19 rates. We investigated the following research questions:

- (1) How are COVID-19 cases, state and county sociopolitical features, and institutional characteristics associated with in-person instruction in Fall 2020?
- (2) Are COVID-19 cases, state and county sociopolitical features, and institutional characteristics differentially associated with in-person instruction at 4-year public, 4-year private, 2-year public, and 2-year private institutions?

Review of the Literature

This literature review covers two primary bodies of research related to our analysis. The first is a nascent body of research on how colleges responded to the coronavirus pandemic. Because the pandemic affected colleges more strongly than previous crises, as evidenced by suspensions of in-person instruction and sharp declines in enrollment and employment at many institutions, we focus on COVID-19 responses in this section. The second body of research is broader and examines how colleges and other organizations respond to sociopolitical pressures. Together, these two areas inform our conceptual framework for this paper.

Emergent Research on COVID-19 and Campus Re-opening, Impacts, and Mitigation

The limited research on the impact of COVID-19 on college campuses reopening broadly fits into three categories: institutional decision-making processes, public health implications, and mitigation for education. Factors that may influence institutional decision-making processes include isomorphism, politics, and revenue. For example, Marsicano et al. (2020) posited that institutions exhibited isomorphic behavior (e.g., that institutions facing similar environmental constraints, such as a pandemic, will adopt similar policies or processes, either independently or through imitation to maintain or gain legitimacy among their peers; see DiMaggio & Powell, 1983) in shifting to online instruction in Spring 2020. For the Fall 2020 semester, Collier et al. (2020b) found that having a Republican governor was associated with a lower chance of choosing an online-only mode of instruction, and a Republican legislature was associated with a greater chance of an institution having in-person instruction. Political leadership was linked to the instructional modality of 4-year and 2-year public institutions as well as 4-year private institutions. Similarly, Felson and Adamczyk (2021) found that political features had a stronger relationship with instructional modality than COVID-19 infection and mortality rates did. Castiello and Whatley (2021) found a revenue motive for COVID-19 decision-making: the number of international students enrolled at a given campus positively predicted institutions' decision to teach in-person for Fall 2020.

Other research has focused on the public health implications of campus reopening plans. Several studies have shown that student mobility (on- and off-campus) increased the number of COVID-19 cases on campus and in the surrounding community. For example, students returning to campus for a hybrid or in-person semester (versus remote) was associated with increased COVID-19 incidence in the local area in the 10 weeks after the college reopened (Andersen et al., 2021). Furthermore, 2020 Spring Break travel spread the disease on college campuses and beyond (Mangrum & Niekamp, 2020). Through genomic sequencing, Richmond et al. (2020) determined that students spread the disease to the residents of campus towns, resulting in increased morbidity and deaths for vulnerable populations.

A third focus of COVID-19 studies in the higher education literature is mitigation strategies to support or allow on-campus learning environments. Paltiel et al. (2020) estimated that repeated testing of students could reduce COVID-19 cases to manageable levels. Some institutions, such as Duke University, have engaged in consistent testing, managing tens of thousands of tests during the Fall semester, which helps monitor and control spread (Denny et al., 2020). However, robust testing was not the norm on college campuses in Fall 2020

(Marsicano et al., 2021). For every well-resourced institution like Duke University, there are many less-resourced institutions with much more limited testing capacity.

Political Polarization and Partisanship in the US

Social Identity and COVID-19

Political polarization has divided Americans along party lines (Iyengar et al., 2012) and eroded trust in well-cemented systems like higher education, which has led to policy decisions such as reducing appropriations to public institutions (Dar & Lee, 2014; Taylor et al., 2020). Often, political polarization has less to do with an attachment to an ideology or policy preference and more to do with social identity (Grossman & Hopkins, 2016) that encourages individuals to curate closed social networks, attack “out-group” members (Chen & Rohla, 2018; Iyengar et al., 2012, 2019), and trust the power structures associated with “in-group” leaders (Krupenkin, 2020). Although both parties have experienced polarization, the cultivation of partisan identity has seemingly been stronger for the Republican Party (Hare & Poole, 2014), which has likely been strengthened by cultural homogenization of white people within the Republican Party (Zingher, 2018) and by unified support of President Trump (Doherty et al., 2017; Jones, 2020).

Polling and emergent studies illustrate a link between divergent political identities and compliance related to COVID-19. Compared to those who lean Democratic, individuals who lean Republican have been less likely to view COVID-19 as a major health threat (Tyson, 2020), less likely to wear masks in public (Kramer, 2020), and show a lower intention to get vaccinated (Funk & Tyson, 2020) and engage in vaccination (Ruiz & Bell, 2021). Partisan differences are also correlated to other COVID-19-related policy preferences such as reopening K-12 schools (Menasce-Horowitz, 2020). For higher education, Collier et al. (2020b) found that Republican-led legislatures were associated with a 9 percentage-point increased chance of institutions choosing in-person instruction for Fall 2020. Moreover, while 74% of polled Republicans indicated that colleges were making the “right decision to bring students back to campus” in Fall 2020, just 29% of Democrats felt the same way (Parker et al., 2020).

Partisanship and Higher Education Finances & Decision-Making

Before tensions surrounding COVID-19 arose, political partisanship had been linked with eroding trust in higher education (Doherty et al., 2017), adjustments to state-based financial support (Dar & Lee, 2014; Taylor et al., 2020), and responses to emergent higher education policies, such as tuition-free college (Collier et al., 2019). State and local governments have generally bent to the will of the national party platforms (Hopkins, 2018). Furthermore, partisanship forcefully guides policymaking and sets the terms for subsequent victories (Miller & Morphew, 2017). Given those parameters, we should expect to see a link between partisanship, institutional support (Dar & Lee, 2014; Taylor et al., 2020), and institutional decision-making (Collier et al., 2020b).

Nearly all higher education institutions rely on government support for financial stability (through tax breaks, grants, appropriations, and other political favors). Much of the literature on politics and partisanship in higher education discusses the effects of state leadership and economic factors on state support for public institutions (McLendon et al.,

2009; Okunade, 2004; Tandberg, 2010). During recessions, public colleges expect to see large declines in state appropriations, as higher education is generally considered to be a balance wheel for state budgets (Delaney & Doyle, 2011; Hovey, 1999). Institutions typically respond by increasing enrollment, raising tuition, and/or cutting services. Colleges may also rely on non-resident students who are willing to pay higher tuition prices to plug budget deficits (Jaquette & Curs, 2015), but this option was limited in Fall 2020 due to travel restrictions and regulations making international student enrollment more difficult (Whitford, 2020).

More recent work has examined the relationship between higher education funding and partisan control of state legislatures and governorships. Republican governors and legislatures are typically associated with lower appropriations for public higher education (Dar & Lee, 2014), unless white students are overrepresented (Taylor et al., 2020), suggesting benefits exist for institutions that enroll students who belong to the political “in-group.” In a rare instance, these political pushes and associated benefits were on full public display in a recent letter from the president of Pennsylvania State University explaining the rationale for avoiding mandated COVID-19 vaccinations, “Regulations across the country clearly reflect state-level political realities. State funding of our University requires a two-thirds vote of the Pennsylvania legislature, meaning that our funding relies on strong bipartisan support” (Barron, 2021). Moving past the often-studied intersection of politics and public institutions, Collier et al. (2020b) found associations between state legislature political power and 4-year private institutions’ likelihood of offering in-person instruction. The field’s understanding of the relationship between partisanship or sociopolitical identity and higher education institutional decision-making, particularly for private institutions, is currently limited.

As polarization is generally driven by social identity and not necessarily bounded by policy preferences (Iyengar et al., 2012, 2019) and given that higher education institutions are dependent on the government for financial and non-financial benefits (Fowles, 2014), it stands to reason that institutional decision-making more closely aligns with current power structures. That is, institutions may exhibit behaviors more aligned with the “in-group” to maintain benefits and avoid negative sentiments associated with being part of the “out-group” (see Billig & Tajfel, 1973 for more about “in” and “out” group dynamics) rather than behaving based on their own (non-sociopolitical) policy preferences. Institutions are potentially weighing the short- and long-term risks of opposing current power structures or are already partisan themselves and want to avoid the scrutiny of being part of the “out-group.” Given that the Democratic and Republican parties hold partisan preferences around both the state of higher education in the United States (Parker, 2019) and policy responses to COVID-19 (Corder et al., 2020; Holman et al., 2020), we might expect differential responses to COVID-19 based on the political characteristics of an institution’s locale (see Collier et al., 2020b; Felson & Adamczyk, 2021).

Hypothesized Model: Building a Framework for Institutional Decision-Making

Our analytical approach expands upon the work developed by Collier et al. (2020b), the first study using the College Crisis Initiative (C2i) dataset to suggest that alignment with state political power structures and risks associated with resource dependency (more so than the state or local severity of COVID-19) was linked with institutional decisions to reopen predominantly in-person in Fall 2020. Figure 1 illustrates our accepted exploratory model for the relationship between sociopolitical features, COVID-19, state revenue

Fig. 1 Accepted model. Robust standardized coefficients reported in Table 5

changes, and in-person reopening—further on, we will discuss alternative specifications that were rejected. Our model includes two latent constructs (*State Sociopolitical Features* and *Pandemic Severity*) and three observed variables (County Political Preferences, State Revenue Changes, and In-Person Instruction). Our thinking is that the developed structure can be applied, tested, and refined on subsequent systemic decisions or shocks to higher education (e.g., Spring or Fall 2021 operations and vaccination or mask mandates). Here, we explain the prior theory and literature based on which we developed this exploratory model.

We tested for a direct link from *State Sociopolitical Features* to County Share of Votes for the GOP candidate in 2016 (from here on out referred to as County Political Preferences) where institutions' campuses were geographically located. An association from *State Sociopolitical Features* to County Political Preferences is based on the idea that local politics have conformed to state-level partisan goals due to political polarization and cultural identification (see Hopkins, 2018). Additionally, as counties look to state governments for guidance on policy and finances (Gold & Ritchie, 1993), this pathway makes sense, considering that county-level governmental factors alone are not always sufficient in influencing economic outcomes (Pink-Harper, 2018). Prior evidence shows that state leadership can adjust policy and rhetoric to prioritize desired political outcomes (Ansolahehere & Snyder, 2006; Cahan, 2019) and engineer social outcomes such as college attainment (see Perna & Finney, 2014).

We generated a direct pathway from both *State Sociopolitical Features* and County Political Preferences to *Pandemic Severity* based upon emergent studies illustrating existing differences between the dominant political parties (Republican and Democratic) and their framing of, and policy responses to, COVID-19 (Dunn, 2020; Hartney & Finger, 2020; Holman et al., 2020). These differences have manifested in divergent views about COVID-19 between citizens who identify as members of each party (Kramer, 2020; Parker et al., 2020; Tyson, 2020). Given that polarization is more of a social identity (Iyengar et al., 2012, 2019), the sociopolitical latent variable predicted the percentage of those

without a 4-year degree. Individuals with less than 4-year degrees often hold distinct views from individuals with higher educational attainment in policy preferences concerning the COVID-19 pandemic. For example, in March 2020, those with 4-year degrees felt COVID-19 is a “significant” crisis (75% versus 66% for those with some college and 61% for those with just a high school diploma; Elfein, 2020). Later on, 82% of those with 4-year degrees were using masks in June 2020 as opposed to 60% with education levels of some college or less (Kramer, 2020). Emergent research has linked these observed state attributes with state-level COVID-19 cases (Chambless, 2020; Frey, 2020).

Additionally, we linked *State Sociopolitical Features*, County Political Preferences, and *Pandemic Severity* to State Revenue Changes. State revenue from taxes was tabulated at the beginning of the pandemic (from March to May 2020) and compared to the same time-frame in 2019 to provide a change statistic (National Public Radio, 2020). Research suggests that lockdowns were influenced by politics, in that Democratic governors were three times more likely than Republican governors to impose a lockdown (Tellis et al., 2020) and were more likely to engage in a lockdown sooner (Corder et al., 2020). States won by Hillary Clinton in 2016 experienced higher per capita infection rates than states won by Donald Trump in March through June 2020. In June, however, the trend converged, resulting in similar infection rates for Democratic and Republican states (Barrow et al., 2020). As such, the combination of *Pandemic Severity* and *State Sociopolitical Features* likely affected early State Revenue Changes. Furthermore, given the lack of a strong federal response to COVID-19, policy decisions were predominantly left to states. State-level policy responses were uneven and sometimes disconnected with COVID-19 conditions (Kettl, 2020).

Finally, we directly linked the latent constructs and observed variables not predicted by latent constructs with the outcome of in-person instruction. Collier et al. (2020b) found a stronger relationship between state political control and instructional modality for Fall 2020 than between COVID-19 case counts and instructional modality. Unlike Collier et al. (2020b) who captured COVID cases at specific dates for all institutions, we calculated COVID-19 cases per capita at the time each institution made its last recorded decision about Fall 2020 instructional modality. We also augment existing work by adding County Political Preferences. Given that the CDC suggests collaboration between local and state health officials (Centers for Disease Control and Prevention, 2020) and institutional leaders have previously asserted they were following the guidelines of local political leaders and government health officials (Bauer-Wolf, 2020), we believe a direct connection between County Political Preferences and our main outcome is appropriate.

Methodology

In our methodology section, we first present our sample and the variables we use to operationalize the accepted model so that the subsequent discussion of the details of our SEM and its latent constructs can use accurate terminology for our work.

Sample

The C2i database houses over 2900 observed institutions. The C2i database does not include private for-profit and certificate-granting institutions, meaning these institution types are not represented in the sample. Institutions were coded into four sectors, 2-year

public, 4-year public, 2-year private, and 4-year private sectors, based on 2018 Carnegie classifications and sector and control variables from the Integrated Postsecondary Education Data System (IPEDS; National Center for Education Statistics, 2020). This resulted in a final sample of $N=2469$ institutions, of which $n=940$ (38%) were 2-year public, $n=902$ (37%) were 4-year private, $n=516$ (20%) were 4-year public, and $n=111$ (4%) were 2-year private institutions. To be noted, 2-year private institutions are included in the analyses, and outcomes are reported. However, due to limitations with sample sizes and concerns related to power (see Wolf et al., 2013)—the rule of thumb for SEM multiple group SEM is $N=100$ per group (Kline, 2005)—we do not spend much time highlighting these outcomes. Still, these outcomes may guide researchers employing analyses with more modest sample size requirements in the future (e.g., simple linear regression).

Variables and Data Sources

Our outcome of interest from C2i data is whether a college planned to have the Fall 2020 term “primarily” or “fully” in person as of September 9, 2020. This represents a college’s final recorded decision for that date, meaning that institutions like the University of North Carolina at Chapel Hill that abandoned in-person instruction in late August are counted as not being in-person. We address concerns about the outcome variable in the Limitations section. In total, 24% ($n=596$) of institutions offered in-person instruction in Fall 2020. By institutional sector, 34% of 4-year private institutions, 27% of 4-year public institutions, 22% of 2-year private institutions, and 13% of 2-year public institutions offered in-person instruction.

We joined the C2i dataset with external data sources to consider multiple variables that prior research suggests may correlate with institutional decision-making (see Castiello & Whatley, 2020; Collier et al., 2020b). We obtained daily COVID-19 cases by state from The New York Times (2020b) and daily COVID-19 cases by county from USAFacts (2020).¹ Cases were chosen primarily because this was the key metric identified by many higher education leaders in making their determinations around instructional mode. Institutions like Paul Quinn College, Duke University, and Purdue University focused on local and national case numbers as benchmarks in determining whether to proceed with in-person instruction (Daniels, 2020; Duke University, 2020; Sorrell, 2020). The COVID-19 data in our analyses reflect case rates at the date each institution made their last known instruction decision from March 1 through September 9, 2020, which was by the time instruction was generally slated to begin at the institution. The earliest decision was made on March 5, 2020, and the latest on September 7, 2020. For state and county cases, our data sources provided a daily cumulative case count, and we calculated a 14-day moving average of new cases per 10,000 residents at the time of the institution’s decision.²

¹ In step with Collier et al. (2020a, 2020b), we chose USAFacts (2020) for county cases because the New York Times county cases database combines all five counties into a single New York City-wide measurement.

² To calculate the 14-day moving average of new COVID-19 cases, we first tabulated the new cases each day (i.e., the 1-day change in cases) from the cumulative case count data. We accomplished this by subtracting the previous day’s cumulative case count from the current day’s cumulative case count within each county/state. To get the 14-day moving average of new cases, we then averaged the 1-day change in cases for the current day and the 13 preceding days. We only generated an average value if there were 14 days of data available, so we do not have a 14-day moving average until the 14th day a county/state reported COVID-19 cases. We generated a 14-day moving average of new cases per 10,000 residents by multiplying the 14-day moving average of new cases in each county/state by 10,000 and then dividing by the county’s/state’s total population.

Next, we turned to the American Community Survey (ACS; U.S. Census Bureau, 2020) to introduce state-level sociopolitical attributes. We used the 2018 5-year estimates, joining the percent of state residents without educational attainment of a bachelor's degree or higher. We also used data from the National Conference of State Legislatures (NCSL, 2020) to identify the states in which both the legislature and governorship were under joint Republican control. This was a binary outcome where 0 = No, 1 = Yes. For county-level political preferences, we imported the share of votes for the Republican nominee for President (Donald Trump) in the 2016 presidential election (Tay, 2018). Using the vote share for a given candidate in a presidential election as a proxy for a county's political disposition is commonplace (see Frey, 2020; Oberhauser et al., 2019). Given that Washington, DC has no governor or state legislature, we opted to drop DC-located institutions from our analyses ($n=8$), which was already factored into our $N=2469$ reported final sample.

As a final component of our main model, we turned to NPR's tabulation of state revenue changes using data from the Urban Institute's State and Local Finance Initiative. In August 2020, NPR calculated the state tax revenue generated in March through May 2020 (a 3-month average) and compared it to the same measure from 2019. Though these data are not specific to state funding for higher education, they provide information about the state's overall financial health at the time that colleges were making decisions for fall 2020 operations. Although state higher education funding ended up being relatively stable in most states in the Fiscal Year 2021, due to federal support and tax revenues being stronger than expected (Laderman & Tandberg, 2021), this was not apparent during the summer of 2020. We hypothesized that changes in state revenue (more specifically, the impact of changes in state revenue on institutions' state appropriations) may be associated with institutions' decisions to offer in-person instruction. Across the U.S., the average change in state tax revenue was -29%. During this timeframe, three states experienced growth: North Dakota (+8%), Nevada (+5%), and South Dakota (+1%). The remaining 47 states experienced state revenue declines, with California (-42%), Alaska (-45%), and Oregon (-53%) experiencing the largest declines (National Public Radio, 2020). We mean-centered this variable before including it in the model. The NPR calculations were missing for New Mexico ($n=30$). Instead of dropping schools from this state, we imputed the data after mean centering, setting these missing values at the average revenue change (i.e., NM schools have a value of 0 for the mean-centered variable).

Development of Latent Constructs

In SEM, variables can be observed or latent. A latent construct is an unobserved variable that can be understood based on information from observed variables. To generate latent constructs for this study, we conducted an exploratory factor analysis (EFA). EFAs are employed when researchers do not have a specific hypothesis about the nature of the underlying factor structure. EFA helps researchers identify clusters of variables that could be grouped and isolate latent constructs from observed variables (Yong & Pearce, 2013). We generated an EFA and identified two latent constructs. We labeled the first construct *State Sociopolitical Features*, which predicted the observed variables of Republican governmental control and the percentage of adults 25 and older without a bachelor's degree or higher. The second latent construct was *Pandemic Severity*, which predicted the observed state and county 14-day average of COVID-19 cases per 10,000 residents on the date of

Table 1 Observed variable R^2

	Baseline model
Observed variables	
State Republican control	0.64
State % without Bachelor's or Higher	0.46
2016 share of County for GOP candidate	0.28
State COVID-19 cases per capita (10k)	0.87
County COVID-19 cases per capita (10k)	0.52
State revenue declines	0.16
In-person instruction	0.05

institutions' last reported decision. Observed variables' R^2 values are reported in Table 1. The R^2 reports the fraction of variance explained by each variable for the outcome variable.

Structural Equation Modeling

Structural Equation Modeling (SEM) directionally examines the direct effect of one variable on another and also captures any indirect effects from one variable passing through another (Klem, 2000). In the past, higher education researchers have used SEM to identify factors influencing first-year college persistence (Collier et al., 2020a), student growth and development (Wofford, 2020), and decisions surrounding expenditures or adoption of new technology (El-Masri & Tarhini, 2017). Relatively few studies have attempted to integrate institutions' contextual sociopolitical factors into SEM structures examining higher education outcomes. Some have explored individual-level attributes like veteran status or partisan political preferences (Gonzalez & Elliott, 2016) or social orientations toward people, community building, and leadership (Harris et al., 2016), but studies leveraging SEM to explore institution-level decisions focus more on institutional characteristics and approaches (Manzoor et al., 2020) or faculty-specific orientations toward pedagogy (Masserini et al., 2019) rather than sociopolitical factors. Our analysis adds nuance in its consideration of state and county features and is the first paper that we are aware of that uses SEM to examine the outcome of in-person instruction during the COVID-19 pandemic.

To use SEM, we remain compliant with several core assumptions highlighted by Kline (2012). First, we maintain temporal sequencing, meaning that the main outcome variable must occur after all observed information. In this case, the main outcome (decision to offer in-person instruction in Fall 2020) occurred after each of the observed variables in the model were measured. Temporal sequencing in SEM limits the possible directions of the relationships examined. *State Sociopolitical Features*, *County Political Preferences*, *Pandemic Severity*, and *State Revenue Changes* were all measured prior to the decision date. The second assumption is that observed variables included in the model must be correlated with the main outcome. As Table 2 illustrates, all observed variables in the models are significantly correlated with the main outcome of in-person instruction.

Third, the proper statistical approach for a SEM analysis must be employed, as there are multiple estimators (e.g., the commonly used Maximum Likelihood Approach [ML]). Because our main outcome was binary, we used a weighted least square means and variance-adjusted approach (WLSMV). The same approach can be found in prior research (Bowman et al., 2019; Collier et al., 2020a). For models with a binary main outcome, a

Table 2 Correlation matrix of variables in reported model

	1	2	3	4	5	6	7
1 Primarily in-person							
2 Republican State control	.10***						
3 % of State without Bachelor's Degree	.06**	.55***					
4 16 county vote to GOP President candidate	.16***	.33***	.35***				
5 14-day average State COVID-19 cases (per capita)	-.05**	.36***	.23***	.08***			
6 14-day average county COVID-19 cases (per capita)	-.06**	.27***	.18***	-.02	.68***		
7 Revenue declines	.09***	.29***	.29***	.27***	.10***	.06**	

$p \leq .10+$, $p \leq .05^*$, $p \leq .01^{**}$, $p \leq .001^{***}$

Table 3 Goodness and badness of fit statistics for invariance tests

Models	CFI	TLI	RMSEA	SRMR
Baseline model	0.993	0.980	0.037	0.023
Constrained loadings	0.995	0.987	0.030	0.023
Constrained intercepts	0.977	0.954	0.056	0.037
Constrained slopes	0.983	0.975	0.041	0.035
Constrained slopes & intercepts	0.925	0.914	0.077	0.061

WLSMV approach is more appropriate than an ML estimator, as the WLSMV has been shown to produce more accurate factor loadings, interfactor correlations, and structural coefficient estimates (DiStefano & Morgan, 2014; Li, 2016). To test our models, we used the Lavaan module found in R. Although SEM studies have recently gained traction, an ongoing debate remains over which measures determine whether the models produce a statistically acceptable fit. For guidance among measures, we leaned on a combination of prior empirical studies published in strong higher education journals (see Bowman et al., 2019; Collier, et al., 2020a) and methodological works (Hu & Bentler, 1998; Xia & Yang, 2019). Methodologists suggest that models are a good (acceptable) fit if the Comparative Fit Index (CFI) $\geq .95$, Tucker Lewis Index (TLI) $\geq .95$, root mean square error of approximation (RMSEA) $\leq .06$, and standardized root mean square residual (SRMR) $\leq .08$ (Hu & Bentler, 1999; Shi et al., 2019).³ Based upon the aforementioned works, Table 3 reports the CFI, TLI, RMSEA, and SRMR statistics for the baseline and constrained models.

Within the SEM framework there are ways to deal with multiple groups. If the groups are not observed, then latent class, or latent profile analysis can help make sense of the data. When there are manifest (observed) groups, such as in this case, multigroup SEM is a way to understand meaningful group differences. This technique also provides a key to knowing whether multigroup analysis is needed through the use of invariance testing. Multigroup SEM allows researchers to obtain a global model fit while being cognizant of the existent manifest groups. Because we hypothesized there were meaningful group

³ Xia & Yang (2019) suggests there is also an optimal fit range when CFI $\geq .98$, TLI $\geq .98$, RMSEA $\leq .03$, and SRMR $\leq .07$ —which our baseline model achieves for CFI, TLI, and SRMR but not RMSEA.

Table 4 Invariance tests

Models	χ^2	df	$\Delta \chi^2$	Δ df	$\text{Pr}(> \chi^2)$	CFI	Δ CFI
Baseline model	52.09	28	–	–	–	0.993	–
Constrained loadings	53.31	34	1.22	6	= .976	0.995	0.001
Constrained intercepts	125.36	43	73.27	15	< .001	0.977	– 0.016
Constrained slopes	118.84	58	66.75	30	< .001	0.983	– 0.010
Constrained slopes & intercepts	337.20	73	285.12	45	< .001	0.925	– 0.068

Bold values indicate baseline comparisons

differences, multigroup SEM is the preferred way to test and analyze these data (Byrne, 2013).

To understand how the four main institutional sectors differ from each other, we conducted invariance testing within a multigroup SEM framework. The purpose of invariance testing is to ascertain whether there are manifest subgroups within the larger population that differ substantially on specific characteristics (Bialosiewicz et al., 2013). To test for differences, we needed to confirm that the model examined the same concepts across groups and to assess whether the structural relationships differed in meaningful ways across those groups (on that aligned model). First, because there is a measurement model, we needed to ensure that there was invariance across groups with respect to factor loadings on the latent variables. In other words, we want to make sure the latent variables are the same for each individual group. If these loadings are significantly different, we cannot say that the latent variables will mean the same thing between groups. Second, we needed to make sure that there were statistically meaningful overall differences between a baseline model where intercepts and regressions are freely estimated and models where the multiple group intercepts and regressions are constrained to equality. We can look at several pieces of evidence to help support our analysis. The first is to examine the Chi-Square statistic. The change in its value and the change in the degrees of freedom between models can let us know whether the constrained model is significantly different from the unconstrained base model (Bollen, 1989; Kline, 2005). A second method of testing invariance is to examine the change in CFI between models (Chen, 2007). Chen suggests that when group sizes are unequal, a change in $\text{CFI} < .005$ indicates invariance, while also considering associated changes in RMSEA and SRMR.

To ensure that our latent variables have the same meaning across groups, the loadings were constrained to equality across groups, and the resulting model fit was compared to the multigroup baseline model. The change in CFI was 0.001 indicating there was no difference in factor loadings on the latent variables between groups. Likewise, a change in Chi-square and the associated degrees of freedom indicated no significant difference between groups ($p = .976$). Altogether these tests indicate that the latent variables present in the model have a shared meaning and it makes sense to treat them as the same latent constructs across the four manifest groups.

Next, the between-group regressions, intercepts, and the combination of regressions and intercepts were constrained to equality to test whether the groups were invariant. The results are presented in Table 4. Briefly, there were statistically significant differences between the constrained and freely estimated models for intercept, regression, and the combination of the two. Likewise, CFI showed meaningful differences between the

freely estimated baseline model and the constrained models, providing further evidence that supported the use of multigroup SEM in this analysis.

Finally, the reported values are robust standardized coefficients (for example, $\beta = .xx$), which report the relative size of the direct or indirect effect on the mean of the tested variable. Standardized coefficients allow for comparisons of variable impact by changing all of the variables to a mean of 0 and then measuring the impact of an increase of one standard deviation in the predictor variable on the tested variable (Kwan & Chan, 2011).

Limitations

As noted, institutional in-person instruction (and pandemic severity) decisions ranged from March 5th, 2020 to September 9th, 2020 and do not fully represent decisions made at the time classes first started (i.e., a range of dates across August and September that are institution-specific). At the time of analysis, the C2i dataset did not include Fall 2020 start dates for all institutions, although it has since become a focus for C2i. At the time of writing this manuscript, C2i had start dates for less than half of the institutions in the dataset. To be sure that our analyses *generally* captured the decision at the start of classes and are not the result of a mass pivot forced by high COVID-19 cases on a campus that attempted to start in-person classes (e.g., UNC-Chapel Hill), we tabulated the number of institutions that made their last on-record decision from August 17 to September 9, 2020. We chose August 17 because that is the date the University of North Carolina moved from being in-person to online, which is arguably one of the more publicized pivots of the Fall semester. During the August 17 to September 9 timeframe, $n = 58$ (6%) 2-year public, $n = 36$ (4%) 4-year private, $n = 22$ (4%) 4-year public, and $n = 7$ (6%) 2-year private institutions made operational decisions. Given that just 5% of the total sample and no more than 6% of institutional sector groups made decisions during this timeframe, we believe our findings *generally* represent effects on the initial plans made in advance of Fall reopening. As an additional robustness check, we excluded the institutions that made later decisions about Fall instructional modality and ran our main model. The fit statistics remained the same as did the significance of variables on the main outcome, although some coefficients experienced minor changes in the point estimate. We performed this same exercise for the sector-specific models and found no differences in fit statistics or trends of significance. In the future, using data that represent the decision by the start of classes (and associated county and state date-dependent COVID-19 data) rather than September 9th should improve our work.

Given the effects of financial pressures on institutional decision-making (see Delaney & Doyle, 2011), we wanted to include additional data on within-2020 budget changes but were unable to do so. We looked at New America's efforts in tracking higher education budget changes (Nguyen et al., 2020) and debated including these data into our model. We decided against it since the information was updated in October (i.e., after institutions made decisions about Fall 2020 instructional modality) and the report only provided data for 44 states. We instead decided to use early state revenue declines for 49 of 50 states (National Public Radio, 2020), even though these data are not specific to higher education budgets. In the coming years, there will likely be more information available on state revenue declines and, specifically, budget cuts to higher education, which we believe should be included in future work.

Table 5 Path coefficients for the Overall Model

		Direct	Indirect	Total
County features	<i>Path</i>			
State features	<i>A</i>	.45***		.45***
Pandemic severity				
State features	<i>B</i>	.52***	– .09***	.43***
County political preferences	<i>C</i>	– .19***		– .19***
State revenue changes				
State features	<i>D</i>	.36***	– .03***	.33***
County political preferences	<i>E</i>	.11***	.01	.12***
Pandemic severity	<i>F</i>	– .06**		– .06**
In-person instruction				
State features	<i>G</i>	.08*	.02***	.10***
County political preferences	<i>H</i>	.13***	.03***	.16***
Revenue declines	<i>I</i>	.04		.04
Pandemic severity	<i>J</i>	– .12***	– .00	– .12***

$p \leq .10$ +, $p \leq .05$ *, $p \leq .01$ **, $p \leq .001$ ***

Slight rounding errors may exist

Finally, one missing attribute in our models may be information about institutions' governing boards (see Morgan et al., 2021). We wanted to include institutional governing board composition, but given the diversity of these boards, lack of information about individual board members' attributes, and how board members are appointed, we could not include the variable in this analysis. These boards may have been a mechanism through which local politics and identities are formalized in campus contexts, constraining the choices of administrators even on rapid-turnaround decisions on which the boards had no observable influence. Our work did not examine this question, but future work could fruitfully explore this possibility. Future research may find value in including governing board attributes when such data exist.

Findings and Discussion

In this section, we first focus on the overall model, which includes all institutions in our sample. Initially we highlight and discuss the findings in the underlying structure (i.e., the relationships between the latent constructs and observed variables leading up to the main outcome) and then focus attention on effects upon the main outcome of offering primarily or fully in-person instruction. Finally, we discuss the findings for four main institutional sectors: 4-year public, 4-year private, 2-year public, and 2-year private institutions. Again, see Fig. 1 for a visual representation of the model and Table 5 for the overall model coefficients. Table 6 contains all direct, indirect, and total path coefficients for the multigroup SEM.

Table 6 Structural equation model examining path coefficients by sector

	4-year public			4-year private			2-year public			2-year private		
	Institutions			Institutions			Institutions			Institutions		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
County features												
State features	.44***		.44***	.51***		.51***	.43***		.43***	.56***		.56***
Pandemic severity												
State features	.59***	-.10***	.49***	.51***	-.15***	-.36***	.51***	-.05**	.46***	.42***	-.10	.31***
County features	-.22***		-.22***	-.29***		-.29***	-.12**		-.12**	-.18***		-.18***
State revenue changes												
State features	.36***	-.01	.35***	.35***	-.02	.32***	.36***	-.04*	.32***	.65***	-.06	.60***
County features	.04	.00	.05	.13***	.01	.15***	.14***	.01+	.15***	.00	.03	.03
Pandemic severity	-.01		-.01	-.04		-.04	-.09*		-.09*	-.15+		-.15+
In-person instruction												
State features	.24**	-.04	.20**	.04	.08***	.12***	-.01	.07***	.06***	-.41+	.18+	-.23
County features	.08	.03	.11*	.22***	.04***	.26***	.21***	.01	.23***	.31*	.02	.33**
Revenue declines	-.01		-.01	.07+		.07+	.01		.01	.14		.14
Pandemic severity	-.13+	.00	-.13+	-.11**	-.00	-.12**	-.09*	.00	-.09*	-.10	-.02	-.12
CFI		1.00			.98			.99			1.00	
TLI		1.02			.95			.99			1.02	
RMSEA		0.00			0.06			0.04			0.00	
SRMR		0.01			0.03			0.02			0.04	

 $p \leq .10$ +, $p \leq .05$ *, $p \leq .01$ **, $p \leq .001$ ***

Slight rounding errors may exist

Overall Model

Underlying Structure

Our main model has identified that *State Sociopolitical Features* ($\beta=.45$) are associated with County Political Preferences, which aligns with research beyond higher education (see Gold & Ritchie, 1993). As partisanship has increased and issues are now more strongly focused through party agendas (Mason, 2018), county-level sociopolitical autonomy has likely been eroded, similar to what occurred between the state and federal levels in that policy decisions may be more a referendum of political and cultural identity and not ideology (Hopkins, 2018; Iyengar et al., 2019). We suggest the underlying structure may be highlighting the tightening of the party and cultural influences over local politics as detailed by Hopkins (2018).⁴

Despite the *State Sociopolitical Features* latent construct and County Political Preferences predicting similar features (i.e., Republican-leaning preferences) their associations with *Pandemic Severity* diverge. Overall, *State Sociopolitical Features* ($\beta=.43$) were positively correlated with COVID-19 per capita cases, whereas County Political Preferences were negatively correlated ($\beta=-.19$). These divergent trends may signal two interesting points. First, although *State Sociopolitical Features* were associated with County Political Preferences, shoring up prior suppositions that local political autonomy may be diminishing (Hopkins, 2018), it is possible that decisions responding to *Pandemic Severity* within counties hosting higher education institutions remained more autonomous from wider political and cultural features.

The second piece may be that institutions in places with certain County Political Preferences made decisions earlier when COVID-19 cases were not relatively high. Guided by Frey's (2020) trends, we generated a correlation matrix between our observed County Political Preferences and institutions selecting in-person instruction by June 1. To be noted, $n=527$ (21%) of institutions in our sample made their last reported decision by June 1; of these institutions, $n=484$ (20% of the total sample; 91% of early deciders) chose in-person instruction. We found a positive correlation between an "early" in-person decision and county GOP vote-share (Pearson's $r=.16$, $p<.001$). This linkage suggests that the same power structures within County Political Preferences also encouraged institutions to make decisions earlier (i.e., without information on the status of the pandemic closer to the schools' opening date), which aligns with our framework of polarization and partisanship encouraging policy preferences (see Collier et al., 2020b; Grossman & Hopkins, 2016; Taylor et al., 2020).

Finally, we found *State Sociopolitical Features* ($\beta=.33$) were positively correlated with State Revenue Changes, meaning state features that predict Republican leadership and below bachelor's education were associated with smaller declines in tax revenue. This outcome makes sense, as states with Republican governors were generally less likely than Democratic governors to employ COVID-19 mitigation tactics which may lead to more severe state revenue declines, such as restricting mobility (Akovali & Yilmaz, 2020) or enforcing lockdowns (Corder et al., 2020; Tellis et al., 2020). Similar to *State Sociopolitical Features*, County Political Preferences ($\beta=.12$) were positively correlated with State

⁴ This outcome may explain why the exploratory model where we tested effects from county to state features were demonstrably weaker and statistically unacceptable.

Revenue Changes, though the magnitude of the coefficient is nearly 3 times smaller. However, the effects on revenue changes were not purely sociopolitically guided. *Pandemic Severity* ($\beta = -.06$) was negatively associated with revenue, albeit to a substantially lower degree than the sociopolitical features. In combination, these findings align with the idea that Republican leaders (represented by larger values for the *State Sociopolitical Features* and *County Political Preferences*) may not have viewed COVID-19 as a threat to the extent of those in the “out-group” (see Tyson, 2020).

Main Outcome of In-Person Instruction

Table 5 shows that three of the four variables had a significant total (direct plus indirect) effect on the main outcome of offering primarily in-person instruction in Fall 2020. County Political Preferences ($\beta = .16$) had the strongest effect on in-person instruction, followed by *Pandemic Severity* ($\beta = -.12$) and *State Sociopolitical Features* ($\beta = .10$). As point estimates were relatively similar for *County Sociopolitical Features* and *Pandemic Severity*, we cannot definitively say that one factor was “more” influential than the other. Given that county and state features were positively associated with the outcome, we again (see Collier et al., 2020b; Felson & Adamczyk, 2021) have evidence of sociopolitical features encouraging behavior aligned with preferences that minimized the severity of COVID-19 (Tyson, 2020). As a reminder, in-person instruction was associated with increased COVID-19 incidence in the local area after a college reopened (Andersen et al., 2021).

Pandemic Severity was the only negative effect on the outcome, which aligns with our expectation that institutions in states and counties with higher infection rates would be less likely to resume in-person instruction. This finding contests prior descriptive research suggesting no clear relationship between COVID-19 cases at either the state or county level and institutional decisions to select in-person instruction (Collier et al., 2020b; Felson & Adamczyk, 2021). However, we remind readers that this paper is different in that we used COVID-19 case rates at the time of an institution’s last recorded decision by September 9, 2020, to develop a latent construct, whereas the former papers generated individual state and county rates based on cumulative totals at specific timeframes. Our findings suggest that in aggregate, institutions were considering and monitoring the severity of COVID-19 (Bauer-Wolf, 2020). Still, this baseline model can mask important differences in how responses to pandemic severity and other pressures differed by institutional characteristics.

Trends Across Institutional Sectors

Our main model answered the question of how sociopolitical, financial, and public health factors were related to in-person instruction in Fall 2020 for all higher education institutions in the sample. Because different sectors of higher education may respond differently to distinct pressures, we also generated separate models for 4-year public, 4-year private, 2-year public, and 2-year private institutions. We hypothesized that we would observe differences between the sectors, given the distinct funding structures and local community integration of the institution types. In this section, we detail and discuss the patterns and contrasts across institutional categories.

When examining these sectors separately, we found significant relationships between in-person instruction and *Pandemic Severity* for 4-year private institutions ($\beta = -.12$) and 2-year public institutions ($\beta = -.09$). While not significant (or could be

considered marginally significant), the coefficient for 4-year public ($\beta = -.13$) institutions did not differ greatly in magnitude from 4-year private institutions. To be noted, we found no significant effects for 2-year private ($\beta = -.12$); but, again, we urge caution given our limitations with this sector. Given that the relationship between *Pandemic Severity* to in-person instruction was not significant for 4-year public institutions, which aligns with Collier et al. (2020b), we interpret this pattern to suggest that public institutions were simply not particularly sensitive to *Pandemic Severity* at the time of decision. While the association between in-person instruction and *Pandemic Severity* is significant for 4-year private and 2-year public institutions, the associations from County Political Preferences to in-person instruction were between 2 times and 3 times stronger.

Next, *State Sociopolitical Features* were significantly related to in-person instruction for 4-year public ($\beta = .20$), 4-year private ($\beta = .12$), and 2-year public ($\beta = .06$) institutions. The effect of State Sociopolitical Features on 4-year public institutions is roughly double that of other institutional sectors. Given the deep body of research on 4-year public institutions and their dependency on state governments (see Delaney & Doyle, 2011; Fowles, 2014) and the effects of polarization on appropriations to 4-year public institutions (Dar & Lee, 2014; Taylor et al., 2020), we expected that 4-year public institutions would be the most sensitive to state-level sociopolitical features and likely strive to remain close to the state-level “in-group.” To be noted, the effects of *State Sociopolitical Features* on 4-year private and 2-year public institutions are mostly driven by indirect effects; thus, illustrating the importance of SEM analyses in these types of examinations. Given these two sectors are sensitive to *State Sociopolitical Features*, each could be making decisions to avoid the risks of losing financial, political, or social support when being perceived as part of the “out-group.”

Additionally, we found a significant association between County Political Preferences and in-person instruction for 4-year private ($\beta = .26$), 2-year public ($\beta = .23$), and 4-year public ($\beta = .11$) institutions. We also found a significant association for 2-year private institutions ($\beta = .33$) but, again, we urge caution with this finding given the weak sample size. Relative to the association between *State Sociopolitical Features* and in-person instruction, the magnitude of the association between County Political Preferences and in-person instruction was nearly 4 times as large for 2-year public institutions and 2 times as large for 4-year private institutions, suggesting that these institutions were more sensitive to localized sociopolitical features. Two-year public institutions have long been dependent on local resources and/or find themselves under local control (Tollefson, 2009), which likely explains the outsized association of in-person instruction with County Political Preferences while exhibiting similar directions as *State Sociopolitical Features* due to the top-down features of polarization (Hopkins, 2018).

It is less clear why we observe significant associations between in-person instruction and both levels of sociopolitical features for 4-year private institutions. Our findings align with prior studies suggesting that private institutions are not quite as politically independent as many would believe (see Collier et al., 2020b; McLendon et al., 2009; Okunade, 2004). What our models may be capturing is a sensitivity of 4-year private institutions towards being part of the sociopolitical “in-group.” Essentially, 4-year private institutions may not want to risk losing political favor and potentially the ability to maintain or increase their market share via matching the cultural identity of their student-constituent market. Furthermore, enrollment-dependent private institutions may recognize the importance of taking cues from state and local policymakers

to maintain an environment (or appearance) of being competitive with public institutions. Prior research has illustrated that for modest public investments, private institutions will accept additional accountability and political oversight (Muller, 1987) and, as such, may be pushed by sociopolitical features to maintain a robust enrollment base and public investment (or political favors; Richardson et al., 1999). Overall, our study affirms that private universities should be considered political actors and illustrates the need for more studies examining how private institutions respond to state and local sociopolitical features.

Alternative Specifications and Future Research

Based on Collier et al. (2020b), we tested alternative models that included elements of prestige and residential characteristics from variables housed within the Integrated Postsecondary Education Data System (IPEDS; National Center for Education Statistics, 2020). The IPEDS data allowed us to examine the effects of institutional characteristics via two latent constructs, supported by Exploratory Factor Analysis (EFA)—see Fig. 2 in the appendix. Variations of this expanded model either did not allow the model to converge, produced unacceptable model fits, or were weaker than the reported models.

The first latent construct we labeled *Prestige Elements*—which consisted of three dummy variables which indicated whether institutions were in a Power 5 sports conference, classified as “Very Competitive” or higher in Barron’s rankings, and whether institutions had at least \$1 billion in their endowments. Based on Collier et al. (2020a, 2020b), we theorized that institutions high in prestige may face different pressures from external stakeholders. The second latent construct, we called *Residential Characteristics*, comprised of two observed variables: percent out-of-state enrollment and percent room capacity. Percent out-of-state enrollment represents the number of first-time undergraduate students who reported a state of residence other than the state in which the institution is located divided by total first-time undergraduate students. Percent room capacity represents an institution’s dormitory capacity divided by total undergraduate enrollment. We thought this latent construct would help account for an institution’s reliance on out-of-state tuition and/or room and board revenues, both of which could influence an institution’s decision to offer in-person instruction due to the (potential) negative financial impact of converting to remote instruction. This baseline model produced weaker CFI = .94, TLI = .91, RMSEA = .05, and SRMR = .05.

A pared-down model eliminating the *Prestige Elements* latent variable produced a stronger model with acceptable CFI = .98, TLI = .96, RMSEA = .05, and SRMR = .03. Each of these fit statistics was weaker than our reported baseline model fit (CFI = .99, TLI = .98, RMSEA = .04, and SRMR = .02). Moreover, the model fits for the sector analyses were generally weaker. To be sure we were reporting the stronger of the two models for the full sample (despite issues with the individual sectors), we used the SBDIFF.EXE program (Crawford & Henry, 2003) to conduct a DIFFTEST between this overall second model and our reported model. The DIFFTEST suggested we report and focus our paper on the stronger overall model. In both models, *Residential Characteristics* had a non-significant association with the outcome of Fall 2020 in-person instruction. Potentially, models including elements of prestige and residential characteristics may be more relevant for decisions related to Spring 2021 reopening, as policy agendas would likely be more cemented, revenue changes and associated effects to institutions would be better known, and institutions

would be more experienced in dealing with COVID-19. We believe our main reported models and the alternative specifications should be re-tested and expanded upon as new information (e.g., campus mitigation strategies) becomes available.

Next, we tested our models with the 2020 Presidential Election results for the county share of votes (New York Times, 2020a) instead of the 2016 vote share. We conducted this sensitivity analysis because an argument could be made that these data from November 2020 may better reflect recent policy preferences and polarization during spring and summer 2020 than an election 3.5 years earlier. These models produced similar fit statistics $CFI=.99$, $TLI=.98$, $RMSEA=.04$, and $SRMR=.02$ and patterns of significant effects, likely due to the stability of political preferences between the 2016 and 2020 elections. We opted to report the model with the 2016 data as it better aligned with our temporal sequencing assumption, given the 2020 election occurred after institutions made Fall 2020 decisions.

We also generated SEM analyses with the percentage of White people in state and counties; however, in every case within various latent variable constructions that predicted the observed variables, the inclusion of percentage of White persons either would not allow the model to converge or produced unacceptable fit statistics—not one model we tested with these variables included produced a model with all four fit statistics being acceptable, which suggests a much weaker model than our accepted structure. For the county level, we see elements of collinearity between the percentage of White people and share of voters for the GOP candidate ($r=.67$, $p<.001$), but the same cannot be said for the state-level correlation between the percentage of White people and Republican control ($r=.16$, $p<.001$). In the end, this study focused on the strongest model we could develop based upon the fit statistics—which did not include the percentage of White people at the state or county levels.

Finally, we tested model specifications that included not just COVID-19 case rates but also COVID-19 death rates at both the state and county levels. Though substituting death rates for case rates produced a model with acceptable fit statistics, the model that includes COVID-19 case rates and excludes COVID-19 death rates was a better fit and remains our preferred model specification. The better model fit and narratives stemming from administrators highlighted in the literature review suggesting that instruction for Fall 2020 was better aligned with cases—such may not be the case for the Spring 2021 semester as more (and arguably) better information surrounding COVID-19 became available. Furthermore, it seems institutions may be again focused on cases for the Fall 2021 semester given the emergence of the more transmissible Delta variant of COVID-19 (Centers for Disease Control & Prevention, 2021). Due to increased cases associated with the Delta variant, California State University at Stanislaus has pushed back the start date of in-person courses to October, faculty at the University of North Carolina have called to shift to an online modality after increased cases in dorms, and Rice University moved online due to false-positive tests (Quilantan, 2021).

Conclusion

As the COVID-19 pandemic hit colleges and universities during the Spring 2020 semester and spread throughout the summer, institutions struggled to make decisions that balanced revenue concerns and politics with public health guidance. This paper used a novel dataset and SEM to examine the relationships between and among our outcome of interest,

in-person instruction in Fall 2020, and sociopolitical, financial, and public health factors. In the overall model, we found that both *State Sociopolitical Features* and County Political Preferences were positively correlated with in-person instruction in Fall 2020. The finding that higher education institutions made decisions tied to county and state sociopolitical conditions is aligned with prior research (see Collier et al., 2020b). More specifically, our multiple group SEM analysis showed that both *State Sociopolitical Features* and County Political Preferences were related to the decision for in-person instruction at 2-year public institutions and 4-year private institutions—but that County Political Preferences were stronger than the effects found from *State Sociopolitical Features*. As such, these institutions relied more heavily on local political preferences than larger ones. We posit that these institutions likely made decisions to avoid being cast as part of the sociopolitical “out-group” to maintain political favors and retain a cultural attachment to their enrollment pool as to not lose enrollment to local or regional competitors (i.e., public institutions or other private institutions). Qualitative work on the decision-making processes of each type of institution is sorely needed to better understand the unique characteristics of the state-/county-to-private institution relationship. Unsurprisingly and shoring up decades of prior research, 4-year public institutions appeared to be most sensitive to the effects of state-level sociopolitical features.

Unlike prior research (Collier et al., 2020b; Felson & Adamczyk, 2021; Marsicano et al., 2020), we found that *Pandemic Severity* was negatively correlated with in-person instruction in the baseline model and for the 4-year private and 2-year public models. Although we find a negative association between *Pandemic Severity* and in-person instruction for 4-year private institutions, we found equally as strong and positive effects for *State Sociopolitical Features* and twice as strong positive effects for County Political Preferences. A similar trend is highlighted for 2-year public institutions. On the other hand, *Pandemic Severity* was just outside of significance for 4-year public institutions, with County Political Preferences exhibiting similar positive effects and *State Sociopolitical Features* effects nearly double. Therefore, while *Pandemic Severity* levied some effect over institutional decisions to engage in-person instruction, our models suggest that, in combination, sociopolitical features likely provided more weight.

Given that in-person instruction was associated with increased COVID-19 incidence in the local area (Andersen et al., 2021), polarization, political identification, and institutions feeling compelled to operate as politicized entities (to stay close to the “in-group”) likely made the severity of the pandemic worse. These outcomes are aligned with the general findings of Collier et al. (2020b) and Felson and Adamczyk (2021), that institutions seemed to give more weight to sociopolitical features over pandemic severity when choosing in-person instruction for Fall 2020. These studies beg the question of sociopolitical fallout for institutions when policymakers, partisans, and the public come to better understand higher education’s role in the pandemic. Given that in-person instruction was heavily favored by Republicans but higher education is a consistent target for partisans and trust in higher education has eroded, institutions’ behavior during the pandemic may have implications for appropriations, regulations, and other policies in the long run. Further research is necessary to understand under what conditions institutions considered public health information, whether there are systematic moderating or mediating factors, and whether the inclusion of structural elements we omitted alters our understanding of the influence of pandemic severity on decisions about instructional modality.

Appendix

See Fig. 2.

Fig. 2 Alternative model with prestige and residential characteristics

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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