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STUDENT SHARE DIFFERENCE: AN APPROACH FOR UNDERSTANDING INEQUALITY WITHIN A STATE SYSTEM

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Introduction

Funding for public four-year colleges and universities is variable across and within states. Some states provide relatively generous direct support for public institutions, while others provide substantially less. Similarly, direct support also varies within states, often based on history, recognition of different missions, or outcomes-based funding formulas. Educational costs also vary within states. Some intuitions and institutional types spend more on education on a per student basis than others, though spending tends to be tightly linked with available revenue. Variable state support and variable per-student spending mean that student tuition covers a higher share of educational costs at some public institutions than at others. Even within the same state, students may be responsible for a higher or lower share of educational expenses depending on where they attend.

Scholars and policy analysts have long focused their attention on questions related to funding for higher education. Considerations include questions about the relationship between educational spending and student success and efforts to determine overall levels of funding adequacy. In this report, we build on those conversations by drawing attention to the relationship between variation in the share of educational expenditures that are covered by tuition, student retention and completion, and institutional inequality, which we understand both financially (meaning differences in levels and sources of income) and socially (meaning differences in status, as measured by admission selectivity) (Taylor & Cantwell, 2019). To do this, we use federal data to develop a novel measure that we term Student Share Difference, or SSD.

We find that SSD is a useful tool for assessing institutional inequality within a state that directly impacts students. As such, the measure of intrinsically interesting for scholars focused on higher education policy, finance, and outcomes. Further, SSD may be useful for policymakers. SSD compares an institution to its public peers within a state rather than to past levels of funding or institutions in other states. This changes the kinds of implications we can draw from our analyses. Rather than recommending that states return to past levels of funding, our analyses suggest ways in which states could spread existing resources and obligations throughout a public higher education system. Reducing institutional financial inequality (as measured by SSD) may help some states to improve student success by identifying the kinds of institutions at which additional funds are most likely to produce results.

Finally, while we understand that SSD is a calculated measure whose interpretation is not always intuitive, we also think it can be useful for students and families surveying the higher education landscape. The utility of SSD derives from the fact that it is hierarchical (positive is “better”) and relative to other public baccalaureate-granting institutions in a state. For prospective students, this gives SSD two analytic advantages over other approaches to studying state funding. First, studying change over time in absolute levels of funding has no practical implication for students, who cannot enroll today in the institutions of the past. Second, studying variation at the institutional level without attention to state context ignores the fact that in-state tuition effectively constrains the choice sets of most students. SSD accounts for both problems because it compares institutions to one another at a given moment in time (not across time) and situates those comparisons within state contexts (i.e., how most students choose a college).

We explore the SSD measure descriptively at both the institutional and state levels. These descriptive analyses help us to understand the ways in which SSD illuminates the landscape of institutional inequality within a state. Next, we use regression methods to address the following question:

- Is SSD associated with measures of student success, including retention and competition rates?

We find suggestive but not conclusive evidence that SSD may contribute positively to student outcomes at some types of institutions.

Based on the findings from this report, we believe that SSD may be a promising metric for further scholarly and policy-focused investigation. Accordingly, we conclude by offering implications for state policymakers and outlining additional ways in which SSD could be used to study state higher education policy.

Background

This report responded to three trends in public higher education policy.

1. Focus on student success as a goal.
2. Volatile finances that left students paying a growing share of core education revenues and complicated the pursuit of that goal.
3. Institutional inequality, as measured both by financial resources and by social status.

In this section, we briefly review background literature on these three trends.

During the 1990s and the first two decades of the 21st century, policymakers from both parties at the federal and state levels, and civil society groups such as think-tanks and philanthropists, emphasized student success as a pressing policy goal (Taylor & Cantwell, 2024a; Haddad, 2021; Mettler, 2014). A strong consensus emerged for the need to promote affordable access to programs that boasted high graduation rates and good post-graduation outcomes. States continue to experiment with various policies to promote affordable access to and improved student outcomes from public higher education. Student success, in other words, emerged as an important goal for higher education systems.

Although student outcomes and affordability varied by state (Heller, 2011), accountably through performance-based funding (sometimes called outcomes-based funding) became a go-to tool for state policymakers nationwide to steer public colleges and universities towards desired outcomes (Kelchen, 2018). Graduation rates have improved in recent decades, but there is little evidence that performance-based funding drove the uptick (Denning et al., 2022; Rosinger, et al., 2023). By contrast, scholars have produced more robust evidence that student success is associated, possibly causally, with educational spending (e.g., Deming & Walter, 2017). Accordingly, states that emphasized accountability and student success might have been expected to increase public spending on higher education. Yet this did not occur. Instead, accountability policies were often accompanied by divestment or performance-based formulas that allocated resources unevenly (Taylor & Cantwell, 2024a). State governments reduced direct funding for higher education over decades, resulting in higher tuition levels at public colleges and universities (Weber, 2017).

Taken together, these trends pointed in the same direction over the first decade of the 21st century. The burdens of funding public higher education shifted from states to individuals. In 2023, around $4 out of every $10 dollars spent on public higher education came from students, double the level observed in 1980 (Kunkle, 2024).

Divestment reached a nadir in the aftermath of the Great Recession of 2007-2009. Most states reinvested in public higher education in the 2010s (Kunkle, 2024). Reinvestment has provided welcome resources for educational operations that could help to meet student success goals. Coming quickly on the heels of divestment, however, reinvestment has also created a climate in which funding volatility—stark variation from one year to another—is a major topic of scholarly attention (e.g., Doyle et al., 2021; Li, 2017). Volatility makes it difficult for higher education leaders to plan, may contribute to institutional inequality and funding gaps between institutions, and may not arrest tuition price growth because prices go up when state funding drops but are not reduced in years when states reinvest.

These two contemporary trends in state policy for higher education—(1) student success as a goal and (2) funding volatility—make it challenging to identify state-level initiatives that might achieve educational goals. Programs that require increased spending could be funded one year and defunded the next due to a volatile financial environment. Such volatility would make it difficult to produce sustained improvements in student success.

A third characteristic of state systems, institutional inequality, adds further complexity to this difficult problem. We understand institutional inequality as having both financial and social dimensions (Taylor & Cantwell, 2019). Financial uncertainty resulting from funding volatility is difficult for all institutions but may be especially challenging for campuses that rely the most on state funding. As part of their mission to expand educational opportunity, these broadly accessible institutions also tend to serve students who have the lowest baseline likelihood to complete (Crisp et al., 2022). By contrast, high-status research universities are often relatively exclusive. These universities are well positioned to produce good outcomes simply because they primarily admit students who are likely to succeed under almost any circumstances (Taylor & Cantwell, 2019). The relationship between funding and student success therefore may differ across institutions not due to institutional performance, but because of distinct financial and status positions.

As this last phrase suggests, financial inequality among institutions may be amplified by social differences. Colleges and universities are arranged into socially constructed status hierarchies in which some institutions and behaviors are rewarded and others are not (Cantwell et al., 2020). Perhaps no institutional behavior is more closely associated with social status than admission selectivity. The more difficult it is to secure admission to an institution, the more likely that institution is to enjoy high social status (Winston, 1999). To be sure, there are other risks associated with exclusive admissions, from failure to fulfill a broad access mission (Crisp et al., 2022) to political backlash (Baker, 2019). However, these risks have not changed the fact that exclusive admissions are associated with high social status in higher education. Further, as noted in the previous paragraph, selectivity is associated not only with status and social inequality, but also with baseline levels of student success.

To address these concerns, we explored links between student outcomes and financial inequality, as measured by relative tuition dependence within a state. That is, we focused not on the state's total level of spending nor on absolute tuition reliance. Instead, we highlighted the distribution of resources within a state system and its relationship to student success.

A focus on the distribution of student share also recognizes the reality that substantial funding increases may not always be fiscally or politically possible. Because states are required to operate with balanced budgets, a state government might not be able to spend more on higher education without making difficult choices about whether to raise taxes or cut spending in other areas. State leaders could decide to distribute funding more (or less) equally among public institutions in the state without changing total state spending on higher education. Giving explicit attention to institutional inequality helps to identify where funds should be routed to leverage the best results. To this end, we consider the interaction of SSD (a measure of financial inequality in a state) with admission selectivity (a measure of social inequality) to assess whether these two measures of hierarchy jointly explain student success.

The Student Share Difference Measure

We developed the metric Student Share Difference (SSD) to measure these within-system funding inequalities. Our variable was inspired by the student share measure reported in SHEEO's annual State Higher Education Finance (SHEF) report. SHEF's student share measure is extremely useful for demonstrating the portion of higher education expenses that students are responsible for covering. This figure is acutely relevant to students, their families, and policymakers. It also facilitates easy comparison over time and between states. Following that precedent, we measured the share of core revenues that students contribute. Our focus on student share rather than state contributions aligns directly with policy concerns about affordability. We believe this measure will allow policymakers to easily understand distributional concerns and can help to inform policymaking that directs resources to the campuses with a potential for high leverage for achieving state attainment goals.

As with any calculated measure, we faced choices on how to specify SSD. To add transparency to our work, we use Appendix A to explain in detail the way we calculated SSD. We also review some alterative specifications of SSD that we considered and explain why we prefer the SSD measure that we use in this report.

As the name implies, SSD reports the gap between the share of educational revenues that students contribute at a given institution, *i* ,and the share of educational revenues contributed by students across the state, *s*. This lends a different conceptual focus to our analysis than is found in accounts that compare trends over time. Such approaches were highly suitable to studying divestment because they essentially compared the present to the past. Given the realities of funding volatility and institutional inequality, however, we focus instead on variation within a given state at a particular point in time. SSD addresses both concerns by comparing one institution to another within the same state.

- *Volatility*: SSD does not norm a particular funding level and analyze changes from that level over time. Instead, it compares in-state public institutions to one another at a particular point in time. Thus, SSD is suitable for comparison over time regardless of funding volatility because all in-state public institutions are exposed to the same volatility in the same year. This has the virtue of reflecting the landscape in which students selecting among public institutions in a state make their college choices.
- *Institutional inequality*: SSD intrinsically measures financial institutional inequality by comparing public four-year institutions within a state to one another. However, the measure does not account for social institutional inequality. To account for this form of

institutional inequality, we also interact SSD with admission selectivity in a second set of regression models.

Insofar as SSD is meaningfully associated with educational outcomes, it could indicate a policy lever for improving student success that accounts for funding volatility and institutional inequality. Institutions where students are asked to cover a larger (or smaller) than typical share of educational expenses compared with other public institutions within the same state may represent a high leverage opportunity to use targeted state investment to boost student success.

Describing SSD at the Institutional Level

Descriptive analysis is the first, foundational step toward understanding a social phenomenon (Loeb et al., 2017). We therefore began our analysis with an extensive exploration of variation over time in SSD and its component parts. For details on how we calculated SSD and the data and sample that we analyzed, visit Appendices A and B, respectively.

The first step toward calculating SSD, as those appendices specify, was to determine the share of education revenues contributed by students at a particular institution. We termed this the Institutional Student Share (ISS). The average ISS rose modestly over the study period, from 43.2% in 2008 to 47.5% in 2022. Most of this increase happened early in the study period, when state divestment accelerated during and immediately after the Great Recession. By 2010, ISS was about the same (47.6%) as it would be at the end of the study period.

Next, we calculated the share of education revenues contributed by students in a particular state. We termed this the State Student Share (SSS), and it consisted of ISS weighted by an institution's full-time equivalent (FTE) enrollment (consult Appendix A). As might be expected, SSS moved approximately in parallel to ISS. SSS rose from 43.2% in 2008 to 51.2% in 2022. As with ISS, that peak was reached in the immediate aftermath of the Great Recession and then maintained for about a decade.

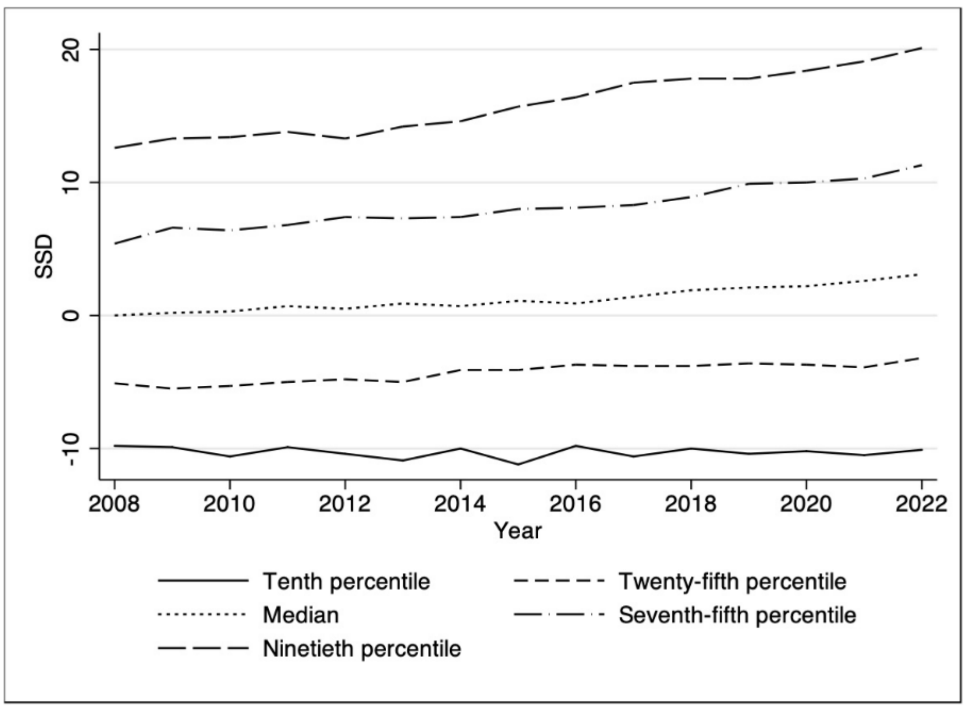
Interestingly, the gap between ISS and SSS—that is, SSD—increased notably over time. Although ISS and SSS followed similar patterns, they did not move at the same rate. As a result, SSD increased over the years, meaning more institutions became less tuition dependent compared with the enrollment-weighted state average. This is likely because larger enrollment public institutions are generally more tuition dependent than smaller enrollment institutions (Taylor & Cantwell, 2019). As a result, the average SSD rose from 0.2 in 2008 to 3.7 in 2022. The upward trend in SSD may also reflect the state reinvestment that has taken place since the Great Recession in 2007 – 2009. A general description of SSD, along with other characteristics included in our regression analyses, can be found in *Table 1* below.

While we might intuitively expect SSD to average zero annually, it is important to remember that the average value of SSD weights every institution equally. Thus, if most institutions had positive SSDs, the average SSD would be greater than zero. Indeed, for all years of the study, the average SSD was positive, indicating that most institutions were in fact slightly less tuition reliant than the weighted average level of tuition dependence in those institutions' states. The mean increase in SSD therefore does not mean that tuition dependence declined. Rather, the descriptive measures of SSD over the sample indicate that variation in tuition dependence within states increased.

These changes over time suggest that much of the variation in SSD happened in the extremes of the distribution of institutions. That is, dispersion in levels of tuition dependence within states likely increased because of movement among institutions with very high or very low SSDs. The majority of institutions may have followed general trends documented elsewhere (e.g., Kunkle, 2024) by becoming slightly less tuition dependent, leaving changes in the average to reflect movement at the extremes. *Figure 1* below supports this interpretation. As this image illustrates, institutions that were notably less dependent than their states—those at the seventy-fifth and ninetieth percentiles—became even less tuition dependent relative to the enrollment-weighted state mean over time. That is, as states reinvested in public higher education, the financial positions of these institutions and their students improved.

Interestingly, no corresponding improvement was identified at the lower reaches of the distribution. Essentially flat lines describe the twenty-fifth and tenth percentiles in *Figure 1*. Accordingly, this figure provides important descriptive evidence attesting to the importance of institutional inequality when trying to understand student success. On average, states reinvested in public higher education over the 2010s (Kunkle, 2024). Yet this average conceals considerable variation across institutions. Some institutions and their students fared relatively well. For many institutions that were already highly tuition-dependent, however, little changed. Thus, while the average SSD may have moved into positive territory over time, this average was a poor reflection of on-the-ground financial conditions at many public colleges and universities.

FIGURE 1
DESCRIPTION OF CHANGE OVER TIME IN PERCENTILES OF SSD, INSTITUTION-LEVEL ANALYSIS



The regression results presented later in this report provide the most robust guidance to understand how institutional inequality within a state is associated with student outcomes. However, one final piece of descriptive evidence helps to frame these analyses. We also described variation across Carnegie classifications to get a sense of how relative tuition dependence is distributed over different institutional types. We used the 2005 Carnegie classifications because they were the most recent grouping prior to the opening of our study period. These categories, therefore, described our sample as it was at the outset rather than as it became over the study period.

The first trend of interest from this table was the distribution of SSD across institutional types for all years. Although the Carnegie classifications are intended to be descriptive, they are often taken as a de facto status hierarchy with "R1" (very high research activity) universities at the top (e.g., McClure & Titus, 2018). Interestingly, SSD moved in the opposite direction of the hierarchy. That is, SSD generally (though not uniformly) rose as we move down the status hierarchy. High-status R1 universities tended to be more tuition dependent (relative to their state systems) than were lower-status colleges and universities. This partially reflected the fact that large research universities collected revenue from many sources (e.g., sponsored research, auxiliary enterprises) that were not counted as core education revenues under our modified version of SHEEO's definition (consult Appendix A). For our purposes, however, the takeaway was clear. As a group, R1 universities were more tuition reliant (relative to the rest of their state systems) than were more broadly accessible institutions.

A second observation from *Table 1* concerned trends over time. Early in the study period, high-status R1 universities were about as tuition dependent as their state systems overall. Only over time did the average SSD value for R1 universities become negative. This suggested that the mix of revenues at these universities changed notably over time. Given both their low overall SSD values and the negative trend over time, high-status universities merit particular attention when analyzing the relationship between SSD and student success. We return to this theme—the complex interrelationship of institutional financial inequality, institutional social inequality, and student success—in regression analyses.

TABLE 1

MEANS (STANDARD DEVIATIONS) OF SSD FOR FULL SAMPLE AND SELECTED YEARS, BY 2005 CARNEGIE CLASSIFICATION

CARNEGIE CATEGORY	FULL SAMPLE	2008	2015	2022
RESEARCH UNIVERSITY (VERY HIGH ACTIVITY)	-1.4	0.4	-1.3	-3.6
	(8.4)	(7.7)	(8.2)	(8.7)
RESEARCH UNIVERSITY (HIGH ACTIVITY)	-1.1	-0.7	-0.8	-1.0
	(7.0)	(6.5)	(7.2)	(8.0)
DOCTORAL/RESEARCH UNIVERSITY	0.8	0.5	0.3	3.7
	(11.6)	(10.7)	(12.0)	(14.1)
MASTER'S COLLEGE OR UNIVERSITY (LARGER PROGRAM)	-0.5	-3.2	-1.0	3.2
	(13.0)	(10.4)	(13.4)	(13.7)
MASTER'S COLLEGE OR UNIVERSITY (MEDIUM PROGRAM)	5.6	3.2	5.4	8.7
	(10.6)	(9.3)	(10.1)	(11.3)
MASTER'S COLLEGE OR UNIVERSITY (SMALLER PROGRAM)	2.6	-0.1	2.3	7.2

	(13.8)	(11.7)	(14.4)	(15.3)
BACCALAUREATE COLLEGE, ARTS & SCIENCES FOCUS	7.4	2.7	7.2	9.9
	(12.1)	(11.3)	(10.8)	(12.8)
BACCALAUREATE COLLEGE, DIVERSE FIELDS FOCUS	8.2	7.3	6.9	11.4
	(12.2)	(12.2)	(16.3)	(10.8)
BACCALAUREATE/ASSOCIATES COLLEGE	6.3	4.2	7.6	6.5
	(7.4)	(7.3)	(7.2)	(10.5)

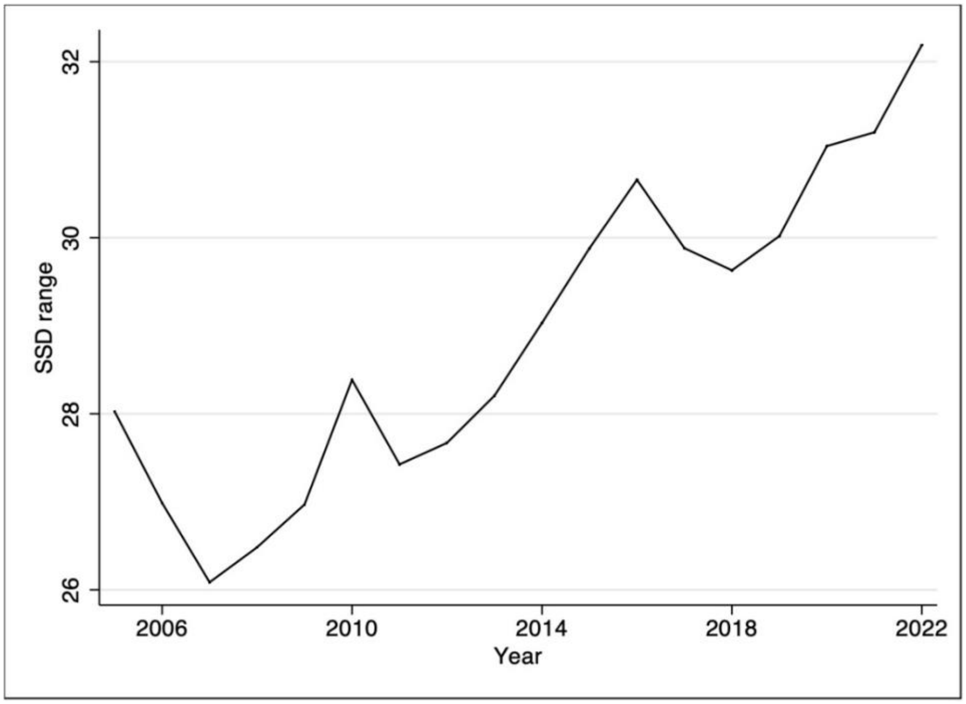
Describing SSD at the State Level

While scholars are intrinsically interested in differences among institutions, state policymakers are responsible only for institutions in their own states. It is therefore also important to consider what SSD can tell us about state systems. After all, while most institutions follow the trends documented in *Figure 1*, these institutions are not randomly distributed across states. Some states may maintain systems where institutions are relatively equally reliant on tuition, while others may create higher levels of inequality. Analyzing SSD at the state level helps to illuminate both differences between states and trends over time within states.

To facilitate these analyses, we created a measure—SSD range—equal to the difference between the least and most tuition-dependent institutions in a state for a given year. In Alabama, for example, the most tuition-dependent institutions in 2022 (relative to the state average for the year) included two large, moderately selective public universities: The University of Alabama (UA) and Auburn University. At the other extreme, Alabama State University, Athens State University, the University of Alabama-Birmingham (UAB) and the University of Montevallo had SSD values between 15 and 20. With the exception of UAB, these findings are unsurprising given the descriptive data on SSD disaggregated by Carnegie classification that we presented in *Table 1*. For state-level analyses, the gap between these institutions, not the institutions themselves, is the primary factor of interest. Accordingly, SSD range is equal to the difference between the two ends of this range. The gap between the least (Alabama State, 20) and most (UA, -12) tuition-dependent institutions in Alabama, relative to that state's average, was 32 points in 2022.

Figure 2 describes the average SSD range across all 50 states, 2006-2022. As this figure indicates, gaps within the average state grew over time. SSD range in the average state increased by about 4 points over these years. The average gap between the minimum and maximum SSD in 2006 was about 28 points, which was approximately the observed value in Florida and Michigan. In 2022, the average range was about the same as the gap in Alabama described in the previous paragraph (32 points).

FIGURE 2
AVERAGE RANGE OF SSD, 2005-2022, STATE-LEVEL ANALYSIS



As in our analysis of institutions, the average may mask substantial variation. Because this variation is likely to be of interest to state-level policymakers, we also traced SSD range within states. We limited this analysis to states with larger higher education systems. States with very few baccalaureate-granting institutions (e.g., Arizona, Delaware, Wyoming) were excluded from this descriptive analysis because their small number of institutions made them highly sensitive to missing data.

Figures 3-7 trace change over time in SSD range for states in the five major accrediting regions: the New England Commission on Higher Education, Middle States Commission on Higher Education (MSCHE), the Southern Association of Colleges and Schools' Commission on Colleges (SACSCOC), the Higher Learning Commission (HLC) and the Northwest Commission on Colleges and Universities (NWCCU). For ease of presentation, we combine California and Hawai'i with states in the latter group rather than displaying them on a separate graph.

Unsurprisingly, the most common state-level pattern mirrored the general trend illustrated in *Figure 2*, a widening range between the highest and lowest SSD values in a state over time. Many states followed some version of this pattern, which was exaggerated in some cases (e.g., Maine) and muted in others (e.g., Montana). Perhaps more interesting were the states in which the range of SSD values were basically flat, including Alaska, Hawai'i, Kentucky, North Carolina, and South Dakota. In these and a handful of other states, gaps in relative tuition dependence did not change much between 2006 and 2022. Finally, a few states, such as Alabama, New York, and Utah, witnessed declines in the range of SSD. This handful of states ran counter to the general trend documented in *Figures 1-2* and so merit further research.

FIGURE 3

SSD RANGE IN PERCENTAGE POINTS, 2005-2022, FOR STATE IN THE NECHE REGION

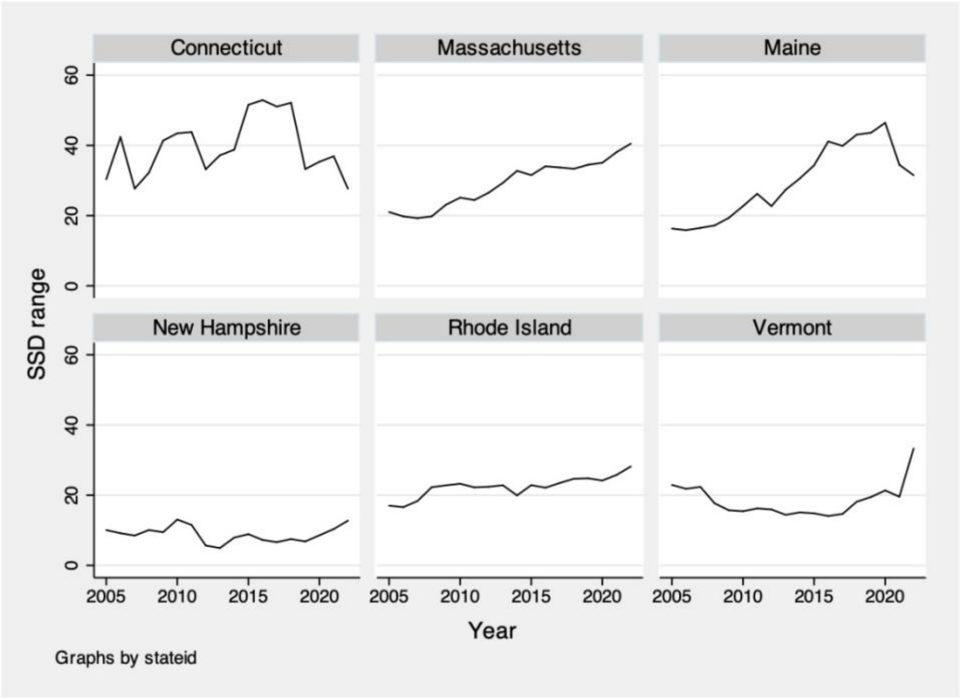


FIGURE 4

SSD RANGE IN PERCENTAGE POINTS, 2005-2022, FOR STATE IN THE MSCHE REGION

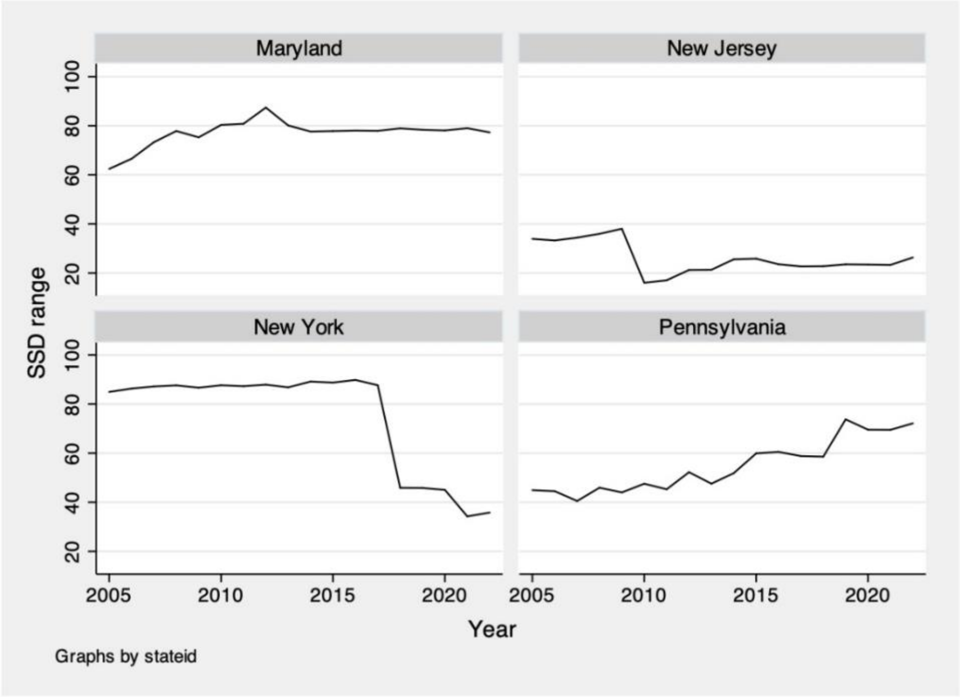


FIGURE 5

SSD RANGE IN PERCENTAGE POINTS, 2005-2022, FOR STATES IN THE SACSCOC REGION

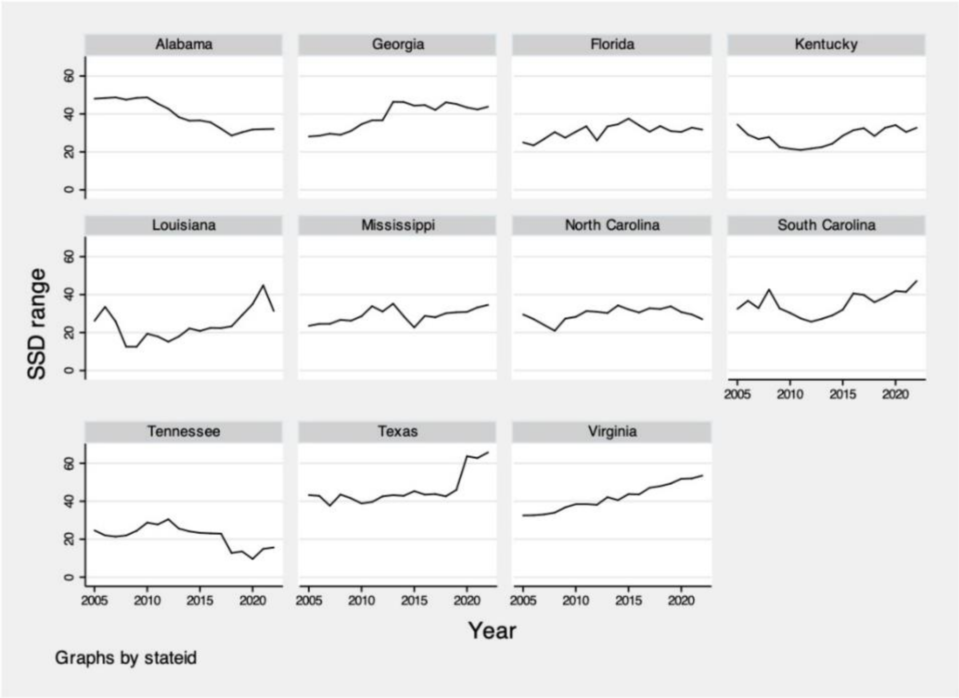


FIGURE 6

SSD RANGE IN PERCENTAGE POINTS, 2005-2022, FOR STATES IN THE HLC REGION

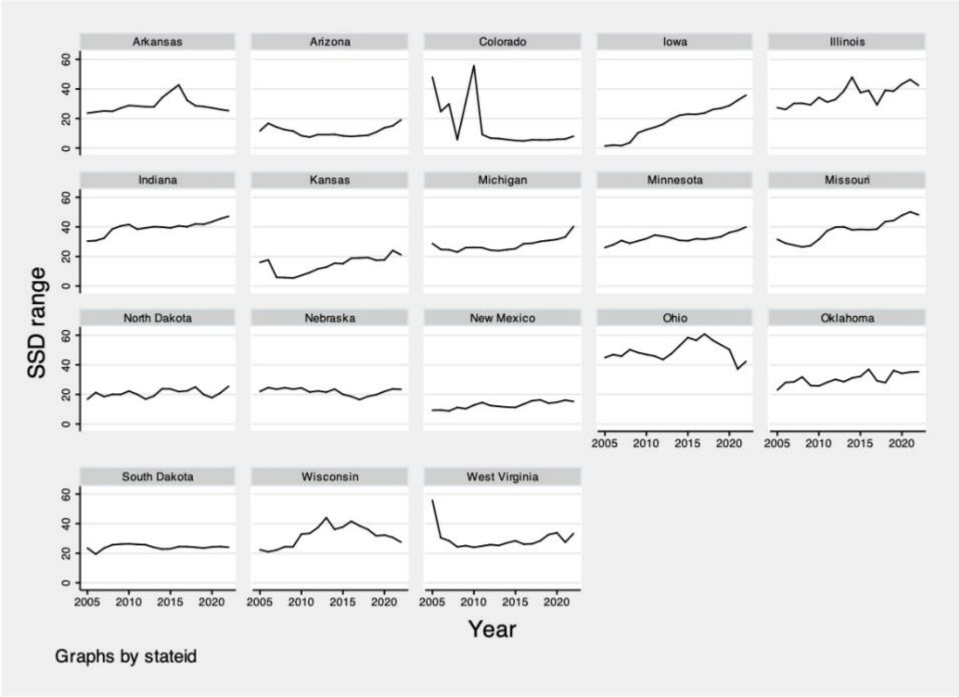
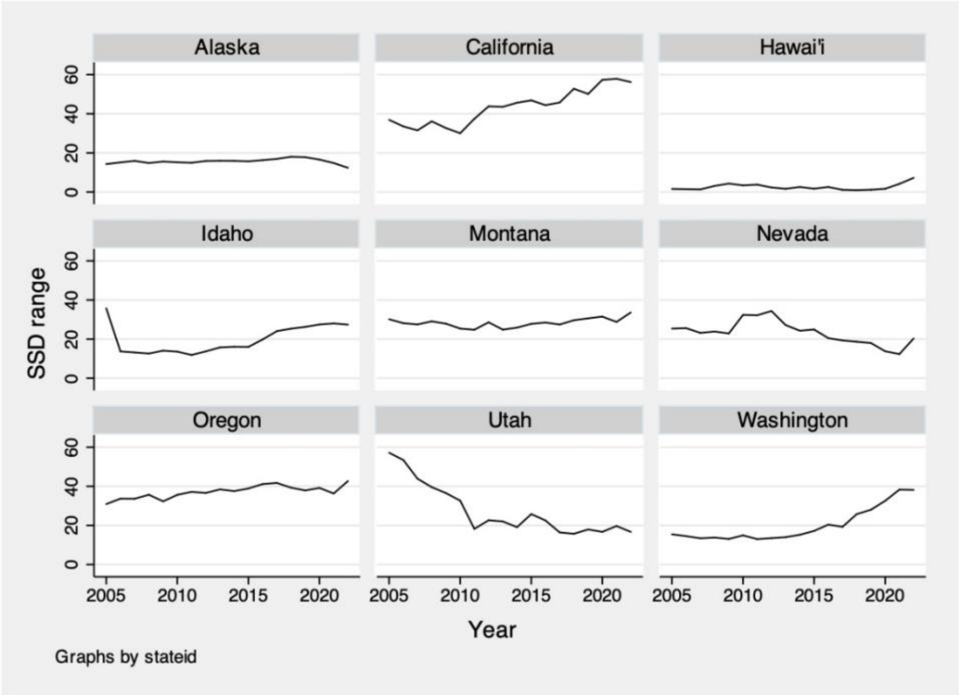


FIGURE 7

SSD RANGE IN PERCENTAGE POINTS, 2005-2022, FOR STATES IN THE NWCCU REGION, CALIFORNIA AND HAWAI'I



A final point on *Figures 3-7* merits attention. Because these figures chart the range of SSD within a state, they start at different points. Thus, for example, both California and Washington followed the general pattern of widening inequality documented in *Figures 1-2*. However, California started with a much higher baseline SSD range in 2006 than did Washington. The absolute gap between the most and least tuition-dependent institutions (relative to the state baseline) was therefore greater in California at all points than it was in Washington.

This is not to say that California's higher education system as a whole was more tuition dependent than Washington's. In fact, the opposite was true. California's state system was less tuition dependent (40.8%) than was Washington's (54.6%) in 2022. SSD is about an institution's tuition reliance *relative to the overall state system*, not absolute tuition reliance. Institutions in Washington were similarly tuition dependent to one another for most years, while those in California demonstrated considerable variation. For both states, however, the gap widened over time. In other words, institutional financial inequality grew.

SSD and Student Success

To explore SSD as a possible policy lever to improve student success, we identified associations between this variable and key outcomes. We explored these associations net of a variety of institution- and state-level control characteristics (refer to Appendix C). Descriptive data on dependent variables and control characteristics appear in *Table 1*. These numbers describe observations with no missing values on any variables of interest, which means that the sample size might differ slightly from that reported in regression tables that employ lags and/or only some variables.

To test the utility of our new measure, we explored associations between SSD and student success. As such, our two dependent variables were established measures of student achievement. First, we studied the rate of retention among first-year students into the second year. For the full sample, the year-to-year retention rate (or, more simply, *retention rate*) for first-time students stood at 75.7% with a modest dispersal around the mean. Mean retention rates changed little over the period, indicating limited improvement across the sample.

Second, we studied the rate of completion within 150% of a baccalaureate program (typically, six years). The average completion rate at 150% of program time (more simply, *graduation rate*) was lower than the average retention rate. This was expected given that students must be retained to graduate but not every retained student is guaranteed to graduate. Completion rate was also more widely dispersed around the mean than was retention rate. That is, sampled institutions varied more widely with respect to graduation than retention.

In a further contrast with retention rate, graduation rates improved nominally, if modestly, over the study period. Over the full sample, the mean 150% completion rate was 51.3%, meaning that slightly more than half of students who entered a degree program at a sampled institution during the study period graduated from that institution within six years of enrolling. In 2008, the mean 150% graduation rate rested at 47.4%. By 2022, it had risen to 55.7%. At the same time, the standard deviation shrank modestly from 16.5 to 15.6 percentage points, suggesting that the boost in completion rates was experienced among a modestly wide swath of the sampled institutions. As in our description of SSD, then, descriptive evidence suggests moderately improved conditions for public higher education over time.

TABLE 2

MEANS (STANDARD DEVIATIONS) OF DEPENDENT AND INDEPENDENT VARIABLES FOR FULL SAMPLE AND SELECTED YEARS

	VARIABLES	(1) FULL SAMPLE	(2) 2008	(3) 2015	(4) 2022
DEPENDENT VARIABLES	RETENTION RATE (FALL TO FALL FOR FULL-TIME FTIC STUDENTS)	75.7%	74.3%	76.6%	75.1%
		(9.8)	(10.0)	(9.5)	(9.9)
	GRADUATION RATE (150% COMPLETION RATE)	51.3%	47.4%	50.7%	55.7%
		(16.5)	(16.4)	(16.9)	(15.6)
INSTITUTION-LEVEL VARIABLES	SSD	1.6	0.2	1.3	3.6
		(11.7)	(10.1)	(12.1)	(12.6)
	TOTAL EXPENDITURES IN MILLIONS	$581.56	$487.03	$577.95	$651.92
		(1024.8)	(807.6)	(985.4)	(1,252.3)

	PCT OF TOTAL EXPENDITURES ON INSTRUCTION	35.7%	33.3%	37.5%	33.3%
		(8.4)	(7.9)	(8.3)	(8.7)
	PCT OF TOTAL EXPENDITURES ON STUDENT SERVICES	8.1%	6.8%	8.6%	8.5%
		(4.1)	(3.4)	(4.1)	(4.6)
	PCT OF APPLICANTS DENIED ADMISSION	29.6%	31.9%	30.6%	22.4%
		(17.7)	(17/0)	(17.3)	(17.8)
	PCT OF UNDERGRADUATES RECEIVING PELL GRANT	35.9%	28.5%	36.8%	33.9%
		(13.1)	(12.2)	(12.9)	(13.0)
STATE-LEVEL VARIABLES	TOTAL STATE POPULATION IN MILLIONS	10.9	10.2	10.9	11.5
		(10.2)	(9.5)	(10.2)	(10.7)
	PERCENT OF STATE POPULATION IDENTIFIED AS WHITE	72.9%	76.3%	74.3%	64.0%
		(11.9)	(10.6)	(10.9)	(14.1)
	PERCENT OF STATE POPULATION HOLDING A BACCALAUREATE DEGREE	30.7%	27.3%	30.2%	35.2%
		(5.8)	(4.9)	(5.2)	(5.5)
	PER CAPITA INCOME IN THE STATE	$37,771.32	$36,988.41	$36,735.30	$41,121.97
		(6,288.5)	(5,167.1)	(5,143.9)	(6,073.0)
	GINI INDEX OF INCOME INEQUALITY IN THE STATE	0.47	0.46	0.47	0.48
		(0.02)	(0.02)	(0.02)	(0.02)
	PCT OF INSURED WHO ACCESS PUBLIC HEALTH INSURANCE IN THE STATE	37.4%	30.2%	38.2%	40.7%
		(5.3)	(4.3)	(4.6)	(4.8)
	NUMBER OF OBSERVATIONS	6,986	460	473	457

One of the key themes of this report, however, is that these general improvements might not be distributed evenly across sampled institutions. To test this possibility, we used regression analyses to explore associations between SSD and our dependent variables. For details on model fit and selection, visit Appendix C. Because student success takes time, these two dependent variables were “led” so that resulting associations linked outcomes to institutional characteristics measured at the time that students began study. Thus, we led retention rate by one year and graduation rate by six years.

Associations between SSD and the dependent variables were estimated net of the control variables described in *Table 2* and Appendix C.

Table 3 reports regression results. As this table indicates, SSD was not correlated with either measure of student success. Instead, student success appeared to be a function of control characteristics. Selective admissions, institutional income and expenditures, the percent of students receiving the Pell grant, and some state characteristics appeared to be better predictors of student success than was SSD. These associations are consistent with prior research.

TABLE 3

RANDOM EFFECTS REGRESSION RESULTS EXPLORING ASSOCIATIONS BETWEEN INSTITUTIONAL AND STATE CHARACTERISTICS AND MEASURES OF STUDENT SUCCESS, 2008-2022

VARIABLES	(1) RETENTION RATE (ONE YEAR LAG)	(2) GRADUATION RATE (SIX YEAR LAG)
SSD	0.00950	0.0105
	(0.0285)	(0.0224)
PCT OF APPLICANTS DENIED ADMISSION	0.0286**	0.0355**
	(0.00870)	(0.0112)
NATURAL LOGARITHM OF NET TUITION AND FEES INCOME	1.786**	1.745*
	(0.569)	(0.856)
NATURAL LOGARITHM OF TOTAL EXPENDITURES	1.520*	1.079
	(0.737)	(0.750)
PCT OF TOTAL EXPENDITURES ON INSTRUCTION	-0.0668**	-0.0272
	(0.0215)	(0.0284)
PCT OF TOTAL EXPENDITURES ON STUDENT SERVICES	0.0988	0.0483
	(0.0692)	(0.0606)
PCT UNDERGRADUATE STUDENTS RECEIVING PELL GRANT	-0.157**	-0.258**
	(0.0280)	(0.0364)
CARNEGIE CLASSIFICATION 2005: RESEARCH UNIVERSITY (HIGH ACTIVITY)	-2.610*	-6.082**
	(1.292)	(1.663)
CARNEGIE CLASSIFICATION 2005: DOCTORAL/RESEARCH UNIVERSITY	-6.242**	-9.672**
	(1.428)	(1.967)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (LARGER PROGRAM)	-5.085**	-10.30**
	(1.605)	(1.777)

CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (MEDIUM PROGRAM)	-5.326**	-9.049**
	(1.802)	(2.344)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (SMALLER PROGRAM)	-5.402**	-8.165**
	(1.906)	(2.288)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, ARTS & SCIENCES FOCUS	-4.396	-8.555**
	(2.485)	(3.141)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, DIVERSE FIELDS FOCUS	-5.526*	-8.757**
	(2.621)	(2.292)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE/ASSOCIATES COLLEGE	-5.392*	-16.08**
	(2.261)	(2.488)
NATURAL LOGARITHM OF TOTAL STATE POPULATION	1.480	1.393
	(1.021)	(0.862)
PERCENT OF STATE POPULATION IDENTIFIED AS WHITE	-0.0491	0.0644
	(0.0279)	(0.0540)
PERCENT OF STATE POPULATION HOLDING A BACCALAUREATE DEGREE	0.434**	0.302
	(0.140)	(0.183)
PER CAPITA INCOME IN THE STATE	-0.000285*	0.000112
	(0.000115)	(0.000171)
GINI INDEX OF INCOME INEQUALITY IN THE STATE	18.36	27.09
	(14.12)	(20.10)
PCT OF INSURED WHO ACCESS PUBLIC HEALTH INSURANCE IN THE STATE	-0.0156	0.154*
	(0.0616)	(0.0661)
FALL TO FALL RETENTION RATE OF FULL-TIME FTIC STUDENTS	-	0.476**
	-	(0.0336)
CONSTANT	-5.934	-78.41**
	(18.58)	(17.95)
OBSERVATIONS	6,568	4,179
NUMBER OF INSTITUTIONS	496	490

Robust standard errors in parentheses
** p<0.01, * p<0.05

The regression reported in *Table 3* estimates the average relationship between SSD and student success, net of control characteristics. As is a consistent theme of our descriptive analyses, however, sample averages can disguise considerable variation. In particular, we have not accounted for the possibility that financial and social dimensions of institutional inequality interact. This potential non-independence makes sense in the context of prior research (e.g., Taylor & Cantwell, 2019) and was suggested by our descriptive analysis (*Table 1*).

Accordingly, *Table 4* reports results of regressions that include a term interacting SSD with admission selectivity. These models accounted for both dimensions of institutional inequality by allowing the relationship between SSD (financial inequality) and student success to vary at different levels of admission selectivity (social inequality). In other words, these models test whether the insignificant results reported in *Table 3* masked more nuanced findings that would become apparent once observations were disaggregated.

The results reported in *Table 4* indicated that this was in fact the case. A chi-squared test of joint significance ($p < 0.01$) confirmed that SSD, admission selectivity, and their interaction were correlated with retention rate. Selectivity and SSD were positively associated with retention, but the interaction term indicated that these benefits attenuated at scale. Similar patterns characterized our analysis of graduation rates in column two. SSD, selectivity, and their interaction were jointly associated with graduation rate ($p < 0.01$). Again, the two main effects were positive and the interaction term was negative.

TABLE 4

RANDOM EFFECTS REGRESSION RESULTS EXPLORING ASSOCIATIONS BETWEEN INSTITUTIONAL AND STATE CHARACTERISTICS AND MEASURES OF STUDENT SUCCESS, 2008-2022

VARIABLES	(1) RETENTION RATE (ONE YEAR LAG)	(2) GRADUATION RATE (SIX YEAR LAG)
SSD	0.0440*	0.0422*
	(0.0190)	(0.0187)
PCT OF APPLICANTS DENIED ADMISSION	0.0320**	0.0377**
	(0.00841)	(0.0107)
INTERACTION: SSD X PERCENT OF APPLICANTS DENIED ADMISSION	-0.00114	-0.000970
	(0.000621)	(0.000642)
NATURAL LOGARITHM OF NET TUITION AND FEES INCOME	1.814**	1.743*
	(0.536)	(0.815)
NATURAL LOGARITHM OF TOTAL EXPENDITURES	1.483*	1.071
	(0.712)	(0.723)
PCT OF TOTAL EXPENDITURES ON INSTRUCTION	-0.0637**	-0.0241
	(0.0211)	(0.0285)
PCT OF TOTAL EXPENDITURES ON STUDENT SERVICES	0.0923	0.0435
	(0.0660)	(0.0617)
PCT UNDERGRADUATE STUDENTS RECEIVING PELL GRANT	-0.152**	-0.255**

	(0.0273)	(0.0360)
CARNEGIE CLASSIFICATION 2005: RESEARCH UNIVERSITY (HIGH ACTIVITY)	-2.568*	-6.097**
	(1.274)	(1.640)
CARNEGIE CLASSIFICATION 2005: DOCTORAL/RESEARCH UNIVERSITY	-6.233**	-9.714**
	(1.403)	(1.935)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (LARGER PROGRAM)	-5.056**	-10.34**
	(1.571)	(1.731)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (MEDIUM PROGRAM)	-5.295**	-9.076**
	(1.783)	(2.323)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (SMALLER PROGRAM)	-5.385**	-8.191**
	(1.877)	(2.259)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, ARTS & SCIENCES FOCUS	-4.384	-8.581**
	(2.482)	(3.122)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, DIVERSE FIELDS FOCUS	-5.549*	-8.841**
	(2.578)	(2.282)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE/ASSOCIATES COLLEGE	-5.412*	-16.14**
	(2.247)	(2.465)
NATURAL LOGARITHM OF TOTAL STATE POPULATION	1.446	1.386
	(1.036)	(0.869)
PERCENT OF STATE POPULATION IDENTIFIED AS WHITE	-0.0460	0.0650
	(0.0284)	(0.0541)
PERCENT OF STATE POPULATION HOLDING A BACCALAUREATE DEGREE	0.455**	0.302
	(0.142)	(0.182)
PER CAPITA INCOME IN THE STATE	-0.000302**	0.000110
	(0.000116)	(0.000171)
GINI INDEX OF INCOME INEQUALITY IN THE STATE	18.32	26.22
	(14.06)	(20.02)
PCT OF INSURED WHO ACCESS PUBLIC HEALTH INSURANCE IN THE STATE	-0.0192	0.150*
	(0.0615)	(0.0660)

FALL TO FALL RETENTION RATE OF FULL-TIME FTIC STUDENTS	-	0.473**
	-	(0.0343)
CONSTANT	-5.601	-77.61**
	(18.59)	(17.75)
OBSERVATIONS	6,568	4,179
NUMBER OF INSTITUTIONS	496	490

Robust standard errors in parentheses
** p<0.01, * p<0.05

Interactions of two continuous variables can be difficult to interpret in detail. Regression results clearly indicated that the returns to SSD were moderated by admission selectivity, but beyond that, it is difficult to say more when relying solely on numerical interpretation. Accordingly, we simplified admission selectivity by creating three groups of institutions:

- *Less selective* institutions denied admission to a small share of their applicant pools, which we defined as less than the mean minus one standard deviation (13.9% of cases).
- *More selective* institutions denied admission to a large share of their applicant pools, which we defined as more than the mean plus one standard deviation (28.3% of cases).
- The remaining observations (i.e., those within one standard deviation of the mean) were classified as *middle selectivity institutions* (57.8% of cases).

We re-ran the regression reported in column two of *Table 4* using these simplified definitions of admission selectivity. Results substantially paralleled the more detailed model presented above, and were robust to alternative specifications (consult Appendix D). SSD, admission selectivity, and their interaction remained jointly significant. The interaction of SSD with admissions selectivity was now substantially easier to interpret. This interpretation appears in *Figure 8*.

FIGURE 8

PREDICTED RELATIONSHIP BETWEEN SSD AND GRADUATION RATE AT THREE DIFFERENT LEVELS OF ADMISSION SELECTIVITY

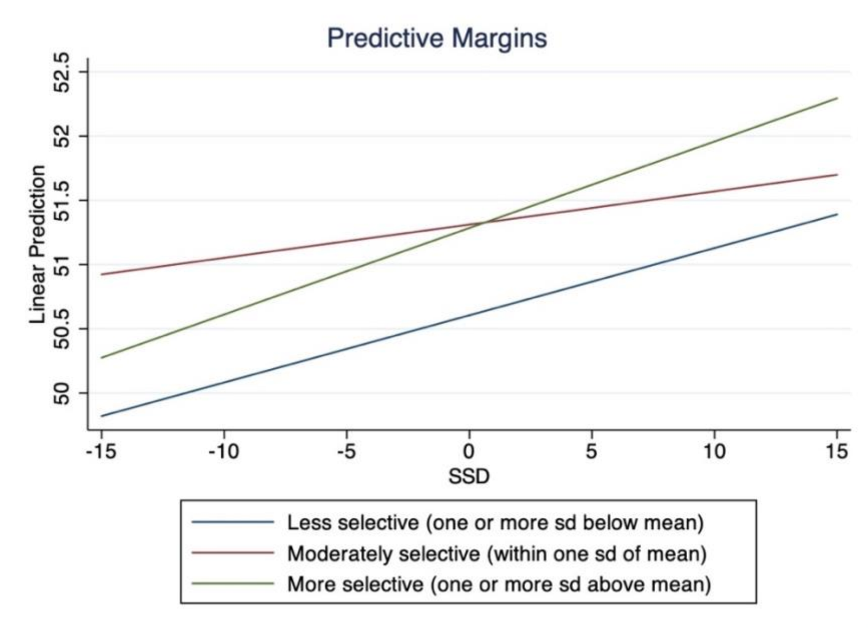


Figure C1 (found in Appendix C) reproduces *Figure 8* with confidence intervals around predicted relationships. Most observations were, of course, clustered in the center of the distribution of SSD (i.e., around zero). Unsurprisingly, then, our model's predictions became more confident as SSD approached zero and less confident as it moved toward extreme values. Accordingly, we limit our interpretation to the range (SSD varying from -15 to +15) within which we can confidently draw inferences. This range is illustrated in *Figure 8*.

Figure 8 indicates that institutions in all groups were expected to improve student success as SSD increased (i.e., as they became less tuition reliant relative to other institutions in the state). This finding makes intuitive sense. More interestingly, the rate of this increase varied notably across the three groups.

Most institutions belonged to the middle selectivity group. For these institutions, there was a gently positive relationship between SSD and graduation rate. That is, as a middle selectivity institution's students bore a smaller share of cost burdens relative to peer institutions in the state, those institutions were expected to witness only very small increases in graduation. Moving from the extreme low to extreme high of SSD was expected to net less than a single percentage point of improvement in graduation rate. While this relationship is statistically distinct from zero, we are uncomfortable concluding that it is substantively important. For practical purposes, the relationship between SSD, admission selectivity, and student success at these middle selectivity institutions is negligible.

The relationship for middle selectivity institutions contrasted with the pattern observed at less and more selective institutions. For institutions in these two groups, SSD was also positively associated with graduation rate. In other words, lower rates of tuition dependence (relative to the state system) were associated with better outcomes at both less selective and more selective institutions. However, the slope of the lines in *Figure 8* is steeper for institutions in these two groups. That suggests that the returns to SSD were better at less and more selective publics than in the middle selectivity group. These relationships might be substantively meaningful as well as statistically distinct from zero.

The slope of the line in *Figure 8* was especially steep for more selective publics. SSD netted slightly higher returns at more selective institutions than at their less selective peers, although this minor difference is not readily apparent in the region depicted in *Figure 8*. Combined with descriptive evidence from *Figure 1* and *Table 1*, this suggests the importance of attending to high-status universities when attempting to steer higher education toward the pursuit of public priorities such as student success.

The points at which the three lines intersected underscored this point. More selective institutions were expected to have *lower* graduation rates than middle selectivity institutions when both groups had SSDs below zero. In other words, middle selective institutions on average produced slightly better outcomes than did more selective institutions when tuition dependence was high (i.e., SSD was low). The relationship reversed above zero, with more selective institutions expected to have better graduation rates. This indicated that, on average, more selective institutions produced better student success outcomes than middle selectivity institutions when tuition dependence was below the state average (i.e., SSD was high).

Middle selectivity and less selective lines did not intersect but moved toward one another as SSD approached +15. In other words, under most conditions, middle selectivity institutions produced better graduation rates than did less selective institutions—an expected finding given the close association between selective admissions and student outcomes (*Table 3*). Yet, when tuition dependence was extremely low (i.e., SSD was extremely high), less selective institutions closed this gap. In other words, public investment that was high enough to reduce tuition dependence to very low levels allowed less selective institutions to perform about as well as their higher status counterparts.

We do not know for sure why the association between SSD and graduation rates is moderated by admissions selectivity. However, we are able to offer a theoretically based explanation. As noted, institutional inequality is both financial and social. Students are sorted into unequal institutions in patterned ways that generally link institutional inequality to the characteristics of student bodies (Taylor & Cantwell, 2019). Students who enroll in less-selective campuses tend to have greater financial need and are able to pay less tuition than students at other institutions. Making these campuses less tuition dependent may yield improved graduation rates in two ways. First, reducing demand for tuition eases the financial burden on students, removing a major barrier to persistence and success. Second, public investment brings in more total resources, and total spending is strongly correlated with student success (Deming & Walter, 2017).

By contrast, the most selective institutions generally admit students who, on average, are able to pay higher tuition fees. Because tuition income comes with few strings attached, highly selective campuses that rely on tuition income may use their resources for purposes other than student support. After all, selective admissions means that students are likely to succeed no matter what an institution does. For these institutions, reducing tuition dependence (relative to the state) may have less to do with finances than with mission discipline. Linking selective public institutions more closely to state governments may create the expectation, either through formal accountability mechanisms or by custom, to use campus resources to support students (see Taylor & Cantwell, 2024 for an expanded conversation on this dynamic).

Implications and Recommendations

This report responded to three documented trends in public higher education. The first was decades of focus on student success as a goal. The second was volatile finances that left students paying a growing share of core education revenues and so complicated the pursuit of that goal. The third was institutional inequality, which meant that both outcomes and student share varied widely from one campus to another.

In response to these three trends, we developed the metric *student share difference* (SSD). SSD calculates the difference between the net share of expenses covered by student tuition and fees at a particular institution (ISS) and the corresponding measure at the state level (SSS). In short, SSD measures whether students pay a relatively high, low, or typical share of educational costs compared to all public four-year students in their state.

Regression results indicated that SSD was a useful predictor of student success. On its own, the measure provided little information. When interacted with admissions selectivity, however, SSD was positively associated with student success. The interaction term attended directly to institutional inequality by allowing the relationship between SSD (financial inequality) and student success measures to vary with institutional status (social inequality).

We graphed these estimated relationships in *Figure 8*. As that figure indicates, SSD was positively and meaningfully associated with student success at less selective and more selective institutions. By contrast, it was only moderately associated with student success at middle selectivity colleges and universities. Indeed, this estimated relationship was so small that it may be substantively meaningless.

These nuanced findings align well with substantive knowledge about college and university behavior. Low-status public colleges and universities are often both mission-focused (Crisp et al., 2022) and poorly resourced (Taylor & Cantwell, 2019). Increasing public investment in these institutions (i.e., increasing SSD and reducing relative tuition dependence) likely provides these institutions with much-needed resources to pursue their missions. Reducing the share of educational expense that students are responsible for contributing has the dual virtues of providing resources to foster good student outcomes and limiting students' financial exposure. A more resource-intensive educational experience that does not place additional pressure on students is an intuitively potent combination for improving student success.

In contrast to these broadly accessible institutions, high-status public universities often seek to redeploy financial resources to improve their status further (Taylor & Cantwell, 2024b). Tuition income is generally unrestricted revenue that can be repurposed toward these status pursuits, such as cross-subsidizing research or investing in the sort of consumption amenities that attract students with the capacity to pay high prices. As such, a high-status institution with a low SSD might be both tuition dependent and relatively in-demand. Under these conditions, there are few incentives to focus on promoting student success. Effort may instead be directed to student recruitment. Reducing the share of income these institutions derive from tuition (i.e., increasing SSD) may not only increase their total income but may also impose restrictions on how funds can be spent. State appropriations, even when they are not earmarked for specific purposes, implicitly come with greater accountability to the public.

For high-status institutions, in other words, the relationship between SSD and outcomes may have less to do with total dollars than with the source of those dollars and the shift in mission implied by this changing mix of revenues.

In summary, our findings suggest that both less selective and more selective institutions produce better student success outcomes as they become more closely linked to state support relative to other campuses in their state (i.e., as SSD increases). However, existing research and theory suggests that the underlying process that produces these similar relationships likely differs. The possibility that sub-sectors of public higher education respond differently to financial incentives and funding models highlights the need for context dependent, nuanced, and flexible policy tools. Further research could explore this possibility to provide additional guidance for state policymakers seeking to understand how system inequality shapes student success.

Our findings are suggestive, but we emphasize that they are exploratory. Therefore, all the inferences and implications following our findings are provisional. Our analyses are fundamentally descriptive, identifying patterns and associations from existing data rather than predicting what will happen in the future (Appendix C). We rely on previous research and our knowledge of the field to provide informed but, ultimately, speculative accounts of the mechanism that may underline the patterns that we observe. More work needs to be done to explore the robustness of SSD before firm conclusions can be drawn.

For now, however, we are confident in offering some guidance to state policymakers based on our findings. First, we urge policymakers to pay attention to the difference in student share among the institutions in their states. Overall, dispersion in levels of tuition reliance has been on the rise (*Figures 1* and *2*). This may leave some high-status universities feeling uncoupled from state priorities while depriving some lower-status colleges and universities of vital resources needed to support student success (*Table 1* and *Figure 8*). Becoming cognizant of institutional inequality is, therefore, a vital skill for educational policymakers. Knowing which intuitions are relatively more or less tuition-dependent is important information that can contribute to decisions about the distribution of state funding. State reinvestment that exacerbates institutional inequality may widen student success gaps despite additional state funds invested in higher education.

Second, and relatedly, we encourage state policymakers to attend to institutional inequality and context when making funding allocation decisions. Targeted investments in particular kinds of institutions may work better than general, system-wide interventions like outcomes-based funding. Based on our findings, and in alignment with previous research, we see investing in broader access institutions – those that admit a high share of applicants – as an especially promising avenue to consider because making these campuses less tuition dependent relative to the state average may net increased graduation rates. Our study provides one more piece of information that investing in board access institutions is one likely effective way to boost student success and state attainment totals. Reinvesting in less selective institutions may provide vital resources that these colleges and universities need to support student success efforts. For different reasons, we also think that policymakers should consider targeted investments in institutions where the student share is relatively high. Shifting the mixture of revenues for more selective institutions may make them more responsive to public priorities.

Even if their underlying realities differ, less and more selective institutions seem to improve student success as they become less tuition dependent and more closely linked to state government funding. At middle selectivity institutions, by contrast, the relationship between SSD and student success was statistically significant but substantively meaningless. Because public dollars are always scarce, we encourage state policymakers to invest those funds where they will further the pursuit of key educational goals—more and less selective institutions. Targeting reinvestment in ways that recognize the complex realities of higher education (e.g., institutional inequality) may help to align scarce state funds more closely with student success goals.

Finally, we believe that SSD may be a useful metric to include in public transparency reporting. SSD may be an important metric to include in state policy briefs and advocacy products when communicating with legislators. Knowing which campuses are relatively dependent on tuition compared to the state average can inform state investment and other policy decisions, as we describe above. SSD may also have some public value. Along with net price, graduation rates, and other key metrics, families that are focused on in-state public higher education options may be interested in knowing how colleges and universities compare to one another. We recognize that SSD is not an especially intuitive measure, and it will take concerted communication and education for it to be well understood and used correctly by decision makers. However, its inherently comparative nature is a good basis from which to build such a communications strategy. Overall, we believe that SSD is a promising measure for further exploration in higher education research and policy analysis.

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Appendix A—Calculating SSD

As a concept, SSD is closely related to the student share variable from SHEEO's annual *State Higher Education Finance* report (SHEF). We could not use SHEF data for our analysis, however, because we needed institution-level figures in order to calculate differences within a state. We therefore engaged in extensive preliminary analyses of institution-level data, drawn from IPEDS, in order to make our measure as closely aligned as possible with the SHEF metric student share.

Defining institutional student share (ISS)

We began with IPEDS measure "tuition and fees after deducting discounts and allowances" (hereafter, *Net T&F*) as a measure of students' and families' contributions. In a supplementary analysis, we subtracted two major federal contributions—the Pell grant and veteran's benefits funded by the Department of Defense (DoD)—to determine whether these funds were included among the "discounts and allowances" that were deducted. The result produced a handful of negative values (i.e., institutions at which Pell+DoD exceeded Net T&F), leading us to conclude that these values had already been deducted.

Having decided that Net T&F was the best indicator of what students and families paid, we sought to determine the denominator over which to allocate student contributions. Because SHEF calculates student share of educational revenues rather than expenditures, we followed a similar course. Our task, then, was to identify non-student sources of revenue and include them in the denominator.

Following SHEF, we focused on state and local contributions. Both entities supported higher education through appropriations, operating grants, and nonoperating grants. Accordingly, we first calculated:

1.1. State contributions = State appropriations + State operating grants and contracts + State non-operating grants and contracts
1.2. Local contributions = Local appropriations + Local operating grants and contracts + Local non-operating grants and contracts

Operating revenues (e.g., state and local revenue provided on an exchange basis, often for a specific project) typically support activities that are *not directly related* to education. Non-operating grants are provided on a non-exchange basis, and so may directly or indirectly support educational activities. Therefore, a more restrictive definition of state and local support might exclude operating grants and contracts from the denominator of student share. Accordingly, we also calculated:

1.3. Restricted state contributions = State appropriations + State non-operating grants

1.4. Restricted local contributions = Local appropriations + Local non-operating grants

We then calculated the share of educational revenues provided by students in two ways that reflect these two denominators:

1.5. Student share = Net T&F / (Net T&F + State contributions + Local contributions)

1.6. Restricted student share = Net T&F / (Net T&F + Restricted state contributions + Restricted local contributions)

Defining state student share (SSS)

To calculate SSD, we needed to compare the two measures of student share (1.5 and 1.6) at a given institution (denoted by the subscript *i*) to the student share at all four-year colleges and universities in that institution's state (denoted by the subscript *s*). Ideally, the latter figure would be provided by SHEF. However, SHEF differed from IPEDS calculations in two key ways that made direct comparisons impossible. First, SHEF excluded medical student tuition, but these funds could not be removed from IPEDS Net T&F data. Second, SHEF's denominator (education revenues) accounted for state student financial aid. However, IPEDS did not report total state student financial aid figures. While we could not devise a workaround for the problem of medical school tuition, we identified two possible substitute measures for state student aid from available variables. We then compared these measures to a naïve calculation that ignored the problem of state student financial aid.

First, IPEDS included a measure that combined federal, state, local, and institutional student financial aid awards (hereafter, *total student aid*). This variable was appealing in its omnibus character. It was limited, however, because institutional aid may represent price discounts rather than revenue from other sources that have been reallocated to education. In other words, the use of this variable might inflate the denominator by reporting forsworn revenue as actual revenue. As a result, using this measure might falsely suppress student share at institutions that engage in high levels of price discounting.

Second, IPEDS reports data on state-funded student financial aid for full-time students who were enrolled in college for the first time (hereafter, *FTFTIC students*). The appeal of this measure was that it excluded institutional student financial aid and could be combined with Pell and DoD to create a denominator that more accurately reflected real educational revenues. The downside of this measure was that it ignored state-funded student aid awarded to everyone except FTFTIC students.

This combination of imperfect measures summarized above left us with six ways to calculate SSD. These approaches reflected the different calculations of institutional student share reported above (1.5 and 1.6), aggregated to the state level. These two equations could be calculated using each of the three adjustments for student financial aid—total student aid, student aid for FTFTIC students, or no adjustment—listed above.

- SSD1: Denominator includes operating revenues and total student aid
- SSD2: Denominator includes operating revenues and state student aid for FTFTIC students, Pell and DoD funds
- SSD3: Denominator excludes operating revenues but includes total student aid
- SSD4: Denominator excludes operating revenues but includes state student aid for FTFTIC students, Pell and DoD funds
- SSD5: Denominator includes only IPEDS T&F, state contributions and local contributions
- SSD6: Denominator includes only IPEDS T&F, restricted state contributions and restricted local contributions

Because we conceptualized SSD based on SHEF's "student share" measure, we compared these six calculations to state data reported in SHEF to determine which was the closest match. While all six measures were internally consistent (i.e., they were calculated in reproducible ways using IPEDS data), we sought external validity through close alignment with the measure of our underlying concept. We used 2022 data, the most recent year for which all variables were available.

Initially, none of the six measures performed particularly well. All six of the student share measures were lower than the SHEF figure of 53%. "Aggregated up" student share varied from about 33% (SSD1) to about 48% (SSD6). Further, all five of the "aggregated up" measures of student share correlated about equally with the SHEF metric (0.76 - 0.81). This moderate level of correlation likely reflected the fact that SHEF aggregates from the individual level (i.e., comparing total tuition income to total education spending in a state) while we calculated at the institutional level. In other words, a simple mean of institutional student shares treated a large institution (25% of state enrollment) and a small one (5% of state enrollment) equally, whereas SHEF's calculation of student share did not.

To address this problem, we weighted institutional student shares by the percentage of FTE in the state that was enrolled at that institution. To do this, we "aggregated up" from IPEDS data to a state-level total FTE. Our calculated state FTE figures correlated very strongly with SHEF data (0.995), suggesting that these weights might improve comparability across the two datasets.

Applying this weight, we re-calculated all six versions of statewide student share, "aggregated up" from IPEDS data. All six calculations again fell below the SHEF figure. As before, SSD6 (naive, excluding non-operating grants) performed best. The difference between the weighted SSD6 calculation (mean 51.1%) and SHEF figure (52.6%) was nominally quite small. For this reason, we elected to use SSD6 as the basis for our calculations.

Calculating SSD

Once we had defined student share at the institutional and state level, it was straightforward to define SSD by subtracting the *Institutional Student Share* (ISS) from the *State Student Share* (SSS). We elected to subtract the institutional student share from the state student share (rather than *vice versa*) to make SSD more intuitive for policymakers. A negative number indicated that a college or university was more tuition dependent than the average institution in the state.

1.7. $SSD_i = SSS_s - ISS_i$

Finally, we extended this definition beyond the pilot year (2022) to encompass all *t* years of our study (Appendix B). The definition of SSD thus became:

1.8. $SSD_{it} = SSS_{st} - ISS_{it}$

Appendix B—Data and Sample

Sample

We began observing sampled colleges and universities using data from 2008, the first year for which American Community Survey (ACS) data on public health insurance were available (refer to Appendix C). The last year of observation was 2022, the most recent year for which all data were available. This span of time included notable historical events (e.g., the Great Recession, the COVID-19 pandemic) that were likely to shape higher education. Including such a wide span of data made our analyses more robust to these historical events.

We defined our sample as public baccalaureate-granting colleges and universities located within a U.S. state, 2008-2022. We identified these institutions using the Carnegie Classifications of 2005, the most recent classification issued prior to the opening of our study. We included 585 public colleges and universities that belonged to one of the following Carnegie categories in 2005:

- Research universities (very high research activity)
- Research universities (high research activity)
- Doctoral/research universities
- Masters colleges and universities (larger programs)
- Masters colleges and universities (medium programs)
- Masters colleges and universities (smaller programs)
- Baccalaureate colleges (arts and science focused)
- Baccalaureate colleges (diverse fields)
- Baccalaureate/associates colleges

We then cross-compared this list with institutions that IPEDS classified as "baccalaureate-granting" in 2005. This eliminated some of the baccalaureate/associates colleges, yielding a final sample of 564 institutions.

Data

We used data from three different sources. Information about institutional finances, enrollments, and student success were drawn from the Integrated Postsecondary Education Data System (IPEDS) of the U.S. Department of Education. Data on state demographic and economic characteristics came from the one-year administrations of the American Community Survey (ACS). The lone exception to this was 2020, for which one-year data were not available. We substituted the five-year administration centered on 2020 (2018-2022) for this year. Finally, as outlined in Appendix A, we used SHEF data as a measure of external validity for our state-level measure of student share.

Appendix C—Analytic methods

Regression techniques are well-suited to identifying associations between a variable of interest and particular outcome. In our case, we were interested in the relationship between SSD and measures of student success. Because SSD compares an institution to its state context, we estimated this relationship of interest net of institution- and state-level characteristics.

In this appendix, we define dependent variables and control characteristics. We then outline the analytic strategy that we used to estimate associations between SSD and our dependent variables, including the use of interaction terms. This strategy was robust to alternative specifications, but was nonetheless limited in important ways. We conclude the appendix by reviewing these limitations.

Dependent variables

We developed two distinct measures of student success from IPEDS data.

1. We calculated the percentage of full-time, first time in college students who began in a given fall semester and returned to the institution the following fall. We refer to this measure as *fall-to-fall retention* or, more simply, *retention rate*.
2. We calculated the percentage of students who entered in a given fall semester and graduated within six years. We refer to this measure as *150% completion rate* or, more simply, *graduation rate*.

These two variables provided distinct but related measures of student success. Students must be retained before they can graduate.

Institution-level control characteristics

A variety of institutional characteristics could be associated with student success at that institution. We carefully justify each control characteristic we used below. While all of the data we used were drawn from IPEDS, we transformed some of these variables in important ways to align them more closely with the underlying concepts of interest.

The first set of institution-level control characteristics accounted for dimensions of financial health not included in SSD. Our primary independent of variable of interest was a function of institutional revenues, which limited our ability to use revenues as control characteristics. We included net tuition income, using the natural logarithm to account for diminishing returns to scale. Beyond this, we relied on expenditure data.

Total expenditures indicated the amount of spending at an institution in a given year. This variable accounted for the strong relationship between spending and student success demonstrated by other scholars (e.g., Deming & Walter, 2017). We controlled total expenditures for inflation using CPI and employed the natural logarithm to account for scale.

We also considered whether spending money on specific functional areas was associated with student success. Accordingly, we included the percentage of total spending devoted to instruction and student support. In contrast to many other institutional operations that serve missions not directly related to student success, these functional areas were explicitly focused on student-related outcomes.

Beyond financial data, our model also accounted for an institution's enrollment characteristics. In particular, we focused on admission selectivity. This measure accounted for the possibility that an institution could improve outcomes by excluding students—that is, by disproportionately enrolling students who were already likely to succeed regardless of institutional effort.

Admissions selectivity served a second purpose in our analysis. Denying admission to applicants has long been an indicator of institutional status (e.g., Winston, 1999). While money is another possible indicator of status, as noted above, these measures tended to be tightly correlated with SSD, which is a function of revenue data. Accordingly, our measure of selectivity introduced fewer modeling concerns. We also reversed this variable—essentially, using "deny rate" rather than "admit rate"—to make regression coefficients intuitive.

We included Carnegie classification 2005 as a series of indicator variables to account for institutional characteristics at the beginning of the study period. On a final note, regressions in which graduation rate was the dependent variable included retention as an independent variable. This control accounted for the sequential nature of student success. Students must persist before they can graduate.

State-level control characteristics

Because SSD relates to state and institutional finances, we also included several state-level characteristics that might covary with student success:

- Total population accounted for the possibility that large states might achieve economies of scale that allowed for more efficient overall generation of outcomes. As with total expenditures, we used the natural logarithm of this measure to account for scale.
- The percent of a state's population identified as white accounted for the possibility that the share of a state's residents who enjoyed social privilege might be correlated with student success.
- The percent of a state's population that held a baccalaureate degree accounted for the possibility that residents who had benefited from higher education themselves might support productive public higher education systems.
- Per capita income accounted for the possibility that states with more robust economies might generally produce better student success measures.
- Gini coefficient of income inequality accounted for financial disparities among a state's residents. We reasoned that a state that was economically unequal might produce a more unequal higher education system.

- Percent of people with health insurance who accessed a public health insurance plan accounted for a state population's general reliance on public support programs.

Analytic strategy

SSD is an inherently comparative measure of institutional financial inequality that indicates an institution's position relative to its counterparts in a state. Accordingly, our substantive interest was *between-institution variance,* meaning comparisons across sampled colleges and universities. This substantive interest meant that the default "fixed effects" approach favored by most policy analysts would not be appropriate for our account. The inclusion of fixed institution-level effects results in a regression based solely on within-institution variance. We therefore opted for a "random effects" (i.e., varying slopes and varying intercepts) regression that analyzes a weighted mean of within- and between-institution variance. We report results from models with fixed state-level effects—allowing between-institution comparisons, conditioned on state—in the *alternative specifications* section in this appendix.

We made several modifications to the standard random effects model in response to our data. First, Drukker's (2003) adaptation of Wooldridge's test revealed serial correlation in our data. Following the advice of Angrist and Pischke (2009), we clustered standard errors one unit "up" in social ordering (i.e., by state rather than by institution).

Second, our dependent variables were indicators of student success. Time is a crucial ingredient of student success. Students must return to college for multiple semesters to graduate. To account for within-institution time of this sort, we "led" our dependent variables, shifting them forward in time relative to the independent variables. Leading the dependent variables estimated associations between independent variables at students' point of entry rather than at the point of exit (i.e., success). Because retention rate measures students from year *t* who returned in year (*t+1*), we led this variable by one year. We led graduation rate by six years because that is the amount of time covered by 150% of a four-year degree plan.

Finally, we accounted for historical time as well as time to degree. As outlined in Appendix B, we designed our sample to span multiple years that included important historical events that shape college-going behavior (i.e., recessions and recoveries). To address historical time, we included a series of dummy variables for each year *t* save one. These "fixed year effects" provided an arithmetic control for macro-level events that shaped sampled institutions' in patterned ways. Because they are of limited theoretical interest, however, we do not report coefficients for these variables in Tables 2 and 3.

Interaction term: Accounting for social institutional inequality

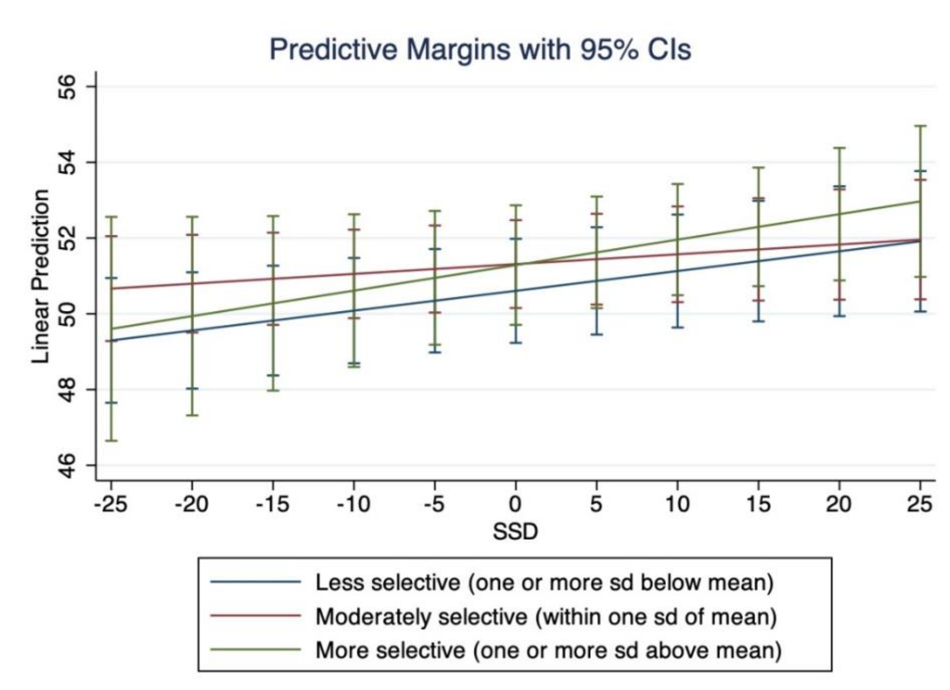
To address institutional inequality, we interacted SSD with admission selectivity. This interaction accounted for the possibility that the relationship between SSD and student success was different at institutions of different social statuses. We conducted chi-squared tests of joint significance to determine whether the interaction improved model fit. We also interpreted interactions graphically for the graduation rate model.

Figure C1 provides a more detailed graphical interpretation of those results. This figure differs in two ways from the more streamlined image found in the main body of the report (*Figure 2*). First, *Figure C1* includes confidence intervals around predictions. These measures of uncertainty help to guide interpretation and generalization. However, they also clutter the graphic. We have therefore omitted them from *Figure 2* but presented them in this methods appendix where interested readers may find them readily.

Second, *Figure C1* spans a wider range on the x axis than does *Figure 2*. Upon reviewing confidence intervals, we determined that predictions on the extreme ends of the x axis (-25 to –15 and 15 to 25) could not be made confidently. Figure 2 in the main body of the text therefore includes only predictions between SSD values ranging from –15 to 15.

FIGURE C1

PREDICTED RELATIONSHIP BETWEEN SSD AND GRADUATION RATE AT THREE DIFFERENT LEVELS OF ADMISSION SELECTIVITY, WITH CONFIDENCE INTERVALS



Alternative specifications

We prefer a random effects regression because it supplies additional information that would be missing from a "fixed effects" approach. That is, if we included state-level fixed effects, we would not be able to estimate parameters for control characteristics that varied at the state level. To have confidence in our random effects model, however, we wanted to compare it to a regression with state-level fixed effects rather than state-level control variables. This approach would combine our interest in between-institution variation with the arithmetic surety that comes from fixed effects regression (Murnane & Willett, 2010).

Table C1 reproduces the regression results found in *Table 3* in the main body of the report. In this supplemental table, however, we have replaced state-level control variables with state-level fixed effects. As with fixed year effects, we do not report results of state-level fixed effects due to their limited theoretical interest.

The results in Table C1 closely conform to those reported in *Table 3*. SSD, admission selectivity and their interaction were not jointly significant in our analysis of retention ($p > 0.05$) but were distinct from zero in our analysis of graduation ($p < 0.01$) rates. We therefore concluded that the results presented in *Table 3* should be interpreted with some caution. Analyses related to retention were less robust to alternative specification than were findings related to graduation rate. We therefore articulate the latter results with greater confidence and focus on these results in graphical interpretation (e.g., Figure 8).

TABLE C1

REGRESSION RESULTS WITH STATE-LEVEL FIXED EFFECTS EXPLORING ASSOCIATIONS BETWEEN INSTITUTIONAL AND STATE CHARACTERISTICS AND MEASURES OF STUDENT SUCCESS, 2008-2022

VARIABLES	(1) RETENTION RATE (ONE YEAR LAG)	(2) GRADUATION RATE (SIX YEAR LAG)
SSD	-0.0248	0.0668*
	(0.0245)	(0.0335)
PCT OF APPLICANTS DENIED ADMISSION	0.00229	0.0411**
	(0.0106)	(0.0123)
INTERACTION: SSD X PERCENT OF APPLICANTS DENIED ADMISSION	-0.000448	-0.00117
	(0.000391)	(0.000734)
NATURAL LOGARITHM OF NET TUITION AND FEES INCOME	1.804*	1.960*
	(0.747)	(0.952)
NATURAL LOGARITHM OF TOTAL EXPENDITURES	0.967	0.744
	(0.948)	(0.763)
PCT OF TOTAL EXPENDITURES ON INSTRUCTION	-0.108*	-0.0177
	(0.0544)	(0.0232)
PCT OF TOTAL EXPENDITURES ON STUDENT SERVICES	0.0628	-0.00650
	(0.0775)	(0.0733)
FALL TO FALL RETENTION RATE OF FULL-TIME FTIC STUDENTS	-	0.474**

	-	(0.0363)
PCT UNDERGRADUATE STUDENTS RECEIVING PELL GRANT	-0.0896**	-0.186**
	(0.0194)	(0.0302)
CARNEGIE CLASSIFICATION 2005: RESEARCH UNIVERSITY (HIGH ACTIVITY)	-2.998**	-6.330**
	(1.138)	(1.709)
CARNEGIE CLASSIFICATION 2005: DOCTORAL/RESEARCH UNIVERSITY	-6.784**	-10.38**
	(1.088)	(1.800)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (LARGER PROGRAM)	-7.222**	-11.62**
	(1.020)	(1.704)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (MEDIUM PROGRAM)	-7.121**	-10.41**
	(1.079)	(2.248)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (SMALLER PROGRAM)	-8.156**	-10.51**
	(1.564)	(2.404)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, ARTS & SCIENCES FOCUS	-6.204**	-10.14**
	(1.676)	(2.802)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, DIVERSE FIELDS FOCUS	-7.119**	-10.74**
	(1.867)	(2.612)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE/ASSOCIATES COLLEGE	-8.131**	-18.35**
	(1.354)	(2.341)
CONSTANT	31.17**	-43.46**
	(11.73)	(11.62)
OBSERVATIONS	4,646	4,640
NUMBER OF INSTITUTIONS	491	491

Robust standard errors in parentheses
** p<0.01, * p<0.05

Limitations

Murnane and Willett (2010) identified conditions under which panel regression results could be given a near-causal interpretation. Our exploratory study does not meet these conditions. We therefore explicitly disavow any causal claims. Our results cannot demonstrate whether SSD is the driving force behind variation in student outcomes. Rather than causally modeling institutional production, we seek to describe past events in a robust manner that accounts for three widely understood characteristics of state higher education systems: attention to student success, financial volatility, and institutional inequality. We hope this exploratory work can guide future research into institution- and state-level conditions that are associated with student success.

Appendix C References

Angrist, D. J., & Pischke, J. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Drukker, D. (2003). Testing for serial correlation in linear panel-data models. *The Stata Journal, 3*, 168-177.

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Appendix D—Selectivity Tiers Regression

For ease of interpretation, *Figure 8* represents SSD interacted with three tiers of admission selectivity rather than the continuous measure of selectivity found in *Table 3*. In this appendix, we report the full regression results on which *Figure 2* is based. Readers will note that it substantially parallels the results found in *Table 3*.

TABLE D1

RANDOM EFFECTS REGRESSION RESULTS EXPLORING ASSOCIATIONS BETWEEN INSTITUTIONAL AND STATE CHARACTERISTICS AND MEASURES OF STUDENT SUCCESS WITH SELECTIVITY MEASURED CATEGORICALLY, 2008-2022

VARIABLES	(1) GRADUATION RATE (LED SIX YEARS)
SSD	0.0523*
	(0.0222)
MODERATELY SELECTIVE	0.706*
	(0.325)
MORE SELECTIVE	0.679
	(0.590)
INTERACTION: SSD X MODERATELY SELECTIVE	-0.0264
	(0.0183)
INTERACTION: SSD X MORE SELECTIVE	0.0150
	(0.0340)
FALL TO FALL RETENTION RATE OF FULL-TIME FTIC STUDENTS	0.431**
	(0.0348)
NATURAL LOGARITHM OF NET TUITION AND FEES INCOME	1.981*
	(0.920)
NATURAL LOGARITHM OF TOTAL EXPENDITURES	1.540
	(0.821)
PCT OF TOTAL EXPENDITURES ON INSTRUCTION	-0.0494
	(0.0367)
PCT OF TOTAL EXPENDITURES ON STUDENT SERVICES	0.0885
	(0.0927)
FALL TO FALL RETENTION RATE OF FULL-TIME FTIC STUDENTS	0.431**
	(0.0348)
PCT UNDERGRADUATE STUDENTS RECEIVING PELL GRANT	-0.258**
	(0.0348)
CARNEGIE CLASSIFICATION 2005: RESEARCH UNIVERSITY (HIGH ACTIVITY)	-5.846**
	(1.786)
CARNEGIE CLASSIFICATION 2005: DOCTORAL/RESEARCH UNIVERSITY	-9.858**

	(2.006)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (LARGER PROGRAM)	-9.794**
	(1.953)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (MEDIUM PROGRAM)	-8.817**
	(2.551)
CARNEGIE CLASSIFICATION 2005: MASTER'S COLLEGE OR UNIVERSITY (SMALLER PROGRAM)	-7.217**
	(2.433)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, ARTS & SCIENCES FOCUS	-8.190**
	(3.110)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE COLLEGE, DIVERSE FIELDS FOCUS	-7.805**
	(2.561)
CARNEGIE CLASSIFICATION 2005: BACCALAUREATE/ASSOCIATES COLLEGE	-14.92**
	(2.424)
NATURAL LOGARITHM OF TOTAL STATE POPULATION	1.540
	(0.905)
PERCENT OF STATE POPULATION IDENTIFIED AS WHITE	0.0422
	(0.0540)
PERCENT OF STATE POPULATION HOLDING A BACCALAUREATE DEGREE	0.389*
	(0.167)
PER CAPITA INCOME IN THE STATE	3.84e-05
	(0.000161)
GINI INDEX OF INCOME INEQUALITY IN THE STATE	26.38
	(18.68)
PCT OF INSURED WHO ACCESS PUBLIC HEALTH INSURANCE IN THE STATE	0.181*
	(0.0713)
CONSTANT	-88.54**
	(18.95)
OBSERVATIONS	4,550
NUMBER OF INSTITUTIONS	518

Robust standard errors in parentheses
** p<0.01, * p<0.05