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Predicting College Closures and Financial Distress

Robert Kelchen*
University of Tennessee – Knoxville

Dubravka Ritter†
Federal Reserve Bank of Philadelphia

Douglas Webber§
Board of Governors of the Federal Reserve

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ABSTRACT

In this paper, we assemble the most comprehensive dataset to date on the characteristics of colleges and universities, including dates of operation, institutional setting, student body, staff, and finance data from 2002-2023. We provide an extensive description of what is known and unknown about closed colleges compared with institutions that did not close. First, we develop a series of predictive model of financial distress, utilizing factors like operational revenue/expense patterns, sources of revenue, metrics of liquidity and leverage, enrollment/staff patterns, and prior signs of significant financial strain. We benchmark these models against existing federal government screening mechanisms such as financial responsibility scores and heightened cash monitoring. We document a high degree of missing data among colleges which eventually close and show that this is a key impediment to identifying at risk institutions. We then show that modern machine learning techniques combined with richer data are more effective at predicting college closures than linear probability models, and far more effective than existing accountability metrics. Such algorithms can greatly improve the predictive accuracy even for institutions with complete data, but are particularly helpful for predicting instances of college financial distress for institutions with spotty data. Finally, we conduct simulations using our estimates to contemplate likely increases in future closures, showing that enrollment challenges resulting from an impending demographic cliff are likely to significantly increase annual college closures for reasonable scenarios.

Keywords: higher education, college, university, enrollment, tuition, revenue, budget, closure, fiscal challenge, demographic cliff

JEL Codes: I22, I23, J21, J24

* A325 Jane and David Bailey Education Complex, 1126 Volunteer Boulevard, Knoxville, TN 37996; e-mail: rkelchen@utk.edu.
† Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA 19106-1574; email: dubravka.ritter@phil.frb.org.
§ Board of Governors of the Federal Reserve, 1850 K St NW, Washington, DC; e-mail: douglas.a.webber@frb.gov.

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I. Introduction

College closures, mergers, and other forms of financial distress can have profound effects not only on students and employees of the affected institutions, but also on local economics – particularly in areas where the institution of postsecondary education serves as an anchor of local economic activity. The postsecondary education sector is facing serious financial headwinds, both due to long-term trends and to post-pandemic recovery. For this reason, measuring and predicting financial distress for these institutions is more important than ever. Yet this endeavor is difficult due to the complexity of their financial structures and the limited availability of suitable data.

One key challenge is declines in enrollment, as the number of students enrolled in degree-granting colleges and universities fell by 15% between 2010 and 2021 (National Center for Education Statistics, 2023). Enrollment declines were particularly stark during the height of the pandemic as individuals chose to participate in a strong labor market over taking classes that were primarily offered online, but participation in higher education was already falling prior to the pandemic. This trend may have finally reversed during the fall 2023 semester, which saw the first across-the-board increase in enrollment in many years (National Student Clearinghouse Research Center, 2024).

Part of these recent enrollment declines is frequently blamed on what is referred to as the "demographic cliff" in higher education, or the decline in the number of high school graduates in parts of the country that is spreading across more states (Bransberger et al., 2020; Grawe, 2018). This has undoubtedly contributed to enrollment declines, and explains a sizeable a portion of the observed enrollment trends. The effect is amplified by low graduation rates and the declining share of high schoolers enrolling in college immediately after graduation, which has fallen from 70% to 62% over the last decade (National Center for Education Statistics, 2023). This decline, which also began before the pandemic, could reflect growing skepticism among the public about the value of higher education (e.g., Brenan, 2023).

The other primary source of students—adult learners—has also seen substantial declines over the last decade. The enrollment of adult learners has traditionally been countercyclical, as potential students seek out community colleges and broad-access private institutions when recessions hit (Barr & Turner, 2015; Hillman & Orians, 2013). The number of students over the age of 25 has fallen by nearly half since the Great Recession (authors' calculations using Integrated Postsecondary Education Data System data), meaning that colleges do not have as large of an alternative market of students to consider when the labor market is strong.

Growing competition for students along with an increasing number of states limiting the tuition-setting authority of public colleges (Kelchen & Pingel, 2024) has limited institutions' ability to increase tuition revenue from existing students. Listed prices for tuition and fees have been at or below the rate of inflation since 2018 following decades of substantial real increases (Ma & Pender, 2023). Tuition discount rates have steadily risen over time, surpassing 50% at private nonprofit colleges in 2022 (National Association of College and University Business Officers, 2023). At the same time, operating costs have also risen quickly due to the pandemic-era inflationary shock and a longer trend of rising benefits expenses (Commonfund Institute, 2023).

These financial pressures on higher education have elevated college closures as a major higher education policy issue. While there have been predictions of a wave of closures for the last decade (e.g., Eide, 2018; Horn, 2018), most colleges survived the pandemic thanks to timely federal support and taking emergency actions to freeze or reduce personnel costs (Natow, 2021). However, the withdrawal of pandemic-era federal funding along with existing stressors has likely resulted in an increase in closures during 2023 (Sanchez, 2024) and into early 2024. There has also been a wave of colleges declaring financial exigency, eliminating academic programs and employees in an effort to cut costs and to avoid potential closures (Ambrose & Nietzel, 2024). Even flagship universities such as West Virginia University and Pennsylvania State University have pursued sizable reductions in the number of academic programs as they face budget deficits (Burke, 2024; Povich, 2023).

Considerable attention has been given to the plight of students attending colleges that close, as it negatively affects the likelihood of students eventually earning a credential (Burns et al., 2023). The potential effects of closures and significant budget cuts can also spill over into the broader communities, as colleges often serve as anchor institutions—economic and cultural engines of their local communities (Birch et al., 2013; Harris & Holley, 2016). Research on the effects of mass layoffs in other sectors has found declines in total regional employment as some workers either move to a new region or drop out of the labor market entirely (Celli et al., 2023; Foote et al., 2019).

In this study, we combine rich data on higher education institutions' students, staff, and financial circumstances with county-level data to explore various forms of fiscal challenges – including full closure – facing institutions of postsecondary education. We focus most closely on strong predictors of closures as the most extreme form of financial distress and one that both college administrators and sector regulators spend considerable resources preventing and addressing. More specifically, we answer the following research questions:

1) To what extent can college financial distress (substantial downsizing or closures) be predicted based on institutional characteristics, enrollment/staff metrics, financial indicators, and local economic conditions in preceding years?
2) What types of institutions may be at risk of financial distress in the future based on reasonable scenarios of enrollment changes and broader economic conditions?

We have assembled the most comprehensive dataset to date on the characteristics of closed institutions compared with institutions that did not close. This paper begins with an extensive description of what is known and unknown about these colleges. The current policy/monitoring solution to predicting the financial distress and closure of institutions – at least at the federal level – is to provide straight-forward and intuitive financial performance metrics that are correlated with closure, but are suboptimal measures from a policy standpoint closure for two reasons: data availability and predictive accuracy. We document a high degree of missing data among colleges which eventually close, show that this is a key impediment to identifying institutions at risk of closure, and also show how modern machine learning algorithms can provide a concrete solution to this problem. These same algorithms greatly improve the predictive accuracy even for institutions with complete data.

For instance, consider three distinct models predicting closure: 1) an OLS model which includes only federal accountability metrics combined with sector and year controls, 2) an OLS model which includes a broader set of financial data and other controls in binned form (to accommodate missing values), and 3) a machine learning model which has the capability of addressing missing data while using the maximum number of variables. To provide but one illustration of improvement in predictive accuracy analysts can expect with carefully employed machine learning methods, consider the 100 institutions with the highest predicted closure probabilities according to each model. Some 47% of institutions actually closed within 3 years using the federal metrics model, 61% of institutions actually closed within 3 years using the OLS model with additional binned controls, and 84% of institutions actually closed using the machine learning model. Finally, we also provide some back-of-the-envelope calculations showing the range of possible future increases in closures if predictions about the severity of the so-called "demographic cliff" are realized.

II. Postsecondary Education Landscape and Fiscal Challenges

In this section, we motivate our study by reviewing the history of financial distress and college closures, as well as consider extant research on factors associated with college closures. We then discuss the relationship between postsecondary education, the labor market, and regional economic growth, examine the role that colleges and universities play as anchor institutions in their local communities, and summarize the current landscape of postsecondary education revenue and expenditure sources.

A. Financial Distress and College Closures

Financial challenges have long played an important role in the history of American postsecondary education. For example, Harvard was able to continue operating in the 1640s and 1650s through fundraising one-quarter of a bushel of corn ("colledge corne") from each local family (Curti & Nash, 1965). College closures also have a long history in America, as roughly 80% of colleges that were ever in operation in the country had closed by 1860 (Tewksbury, 1932). However, an analysis of nearly 500 private nonprofit colleges that were identified as having limited resources in 1972 found that nearly 85% of the institutions continued to operate in some form four decades later (Tarrant et al., 2018). This suggests a substantial amount of resilience in the sector. Public higher education systems, in particular, rarely suffer closures due to local and state financial support, but do sometimes face mergers and consolidations (which are more difficult to observe and outside of the scope of the present study, but a fruitful area for future research).

A number of analysts and consulting firms have identified factors that they view as being indicative of college closures without empirically testing their accuracy (e.g., Denneen & Dretler, 2012; Parthenon-EY, 2017; Zemsky et al., 2020). There is much less research that examines factors associated with a higher risk of closure using econometric or statistical frameworks. Institutional characteristics that are related to closure in statistical analyses include being a Historically Black College or University (HBCU) or a women's college, while being an urban college reduces the likelihood of closure (Britton et al., 2023; Zapp & Dahmen, 2023). Financial characteristics associated with closures include lower faculty salaries, lower tuition, smaller endowments, and higher levels of instructional spending (Bates & Santerre, 2000; Britton et al., 2023; Porter & Ramirez, 2009). Yet many of the factors identified in these studies are not necessarily causing colleges financial distress in and of themselves, but rather are correlated with institutional characteristics and financial indicators predictive of institutional financial distress.

We take inspiration for our study from Kelchen (2020), who used linear probability models to predict college closures within two and four years separately for private nonprofit and for-profit institutions. Some of the key variables associated with closures in that study included declines in enrollment, increases in the tuition discount rate, a decline in endowment values, and triggering Department of Education's monitoring metrics for Title IV eligibility: failing the federal financial responsibility test or being on the more serious level 2 of heightened cash monitoring. While models in Kelchen (2020) were able to identify colleges at the highest risk of closures, only a small fraction of the riskiest institutions closed in the short term.

B. Postsecondary Education, the Labor Market, and Economic Growth

While postsecondary education serves numerous purposes including personal growth, fostering civic engagement, and advancing society, students and policymakers place particular focus on colleges' role in preparing students for the labor market. Students consistently rate getting a good job and making money as some of the most important reasons for going to college (e.g., Stolzenberg et al., 2020), and a growing number of states are explicitly tying public funding for higher education to workforce-related metrics (Kelchen et al., 2024b). And the sizable economic returns for college completers—albeit with significant variation by field of study, student ability, and the price tag of the credential—highlight the importance of higher education in the labor market (Webber, 2016; Zhang et al., 2024).

There is a sizable body of research showing a strong relationship between the availability of higher education opportunities in a local community and economic health. Much of the relationship is due to increased employment because many graduates (particularly at less selective colleges) stay in the area (Conzelmann et al., 2023) and because of the service-related jobs that are associated with having colleges in the area (Lee, 2019). By comparing counties that received public universities to counties that were runners-up for those institutions, research showed that counties with colleges enjoyed higher levels of educational attainment and employment in human capital-intensive industries (Andrews, 2023; Russell et al., 2022). Using the same research design, Russell and Andrews (2022) and Howard et al. (2022) showed increases in economic mobility and local economic resilience in counties with college campuses. Lehnert et al. (2024) found that opening new branch campuses of existing public colleges is associated with significant increases in local economic output.

In other words, higher education institutions often serve an important role for economic development and regional prosperity. This fits into a broader body of literature in the field of education finance regarding the role of sizable employers such as hospitals and colleges as anchor institutions that attract other businesses and help to develop a larger employment base (e.g., Harkavy & Zuckerman, 1999; Harker et al., 2022). There is also work specifically considering the role of higher education as anchor institutions (Birch et al., 2013; Harris & Holley, 2016).

It is also important to emphasize that colleges serve as more than economic engines of local communities. Particularly in more rural and isolated areas, higher education institutions have the potential to function as the cultural hub of communities by supporting civic engagement, the arts, and providing entertainment and educational opportunities (Ashley et al., 2023; Howard, 2014). An important activity of many colleges is noncredit courses, which can serve to develop individuals' skills for the labor market or to simply promote lifelong learning (Arena, 2013; Xu & Ran, 2020). The proximity to colleges has even been a factor in the retirement decisions of some Americans, as they seek out a stimulating environment in their golden years (Smith et al., 2014).

Put together, colleges have the ability to attract individuals to local communities and to better the overall quality of life. For those reasons, struggles of higher education institutions—through closures or cutbacks caused by severe financial distress—are of particular interest to college leaders, researchers, policymakers, and others. They also represent a large part of the motivation behind our analysis to examine the factors associated with closures or severe declines in institutional health.

C. College Funding Metrics and Patterns

The American postsecondary education system today consists of approximately 6,000 colleges and universities that receive federal financial aid under Title IV of the federal Higher Education Act. There is also a substantial number of very small colleges, particularly in the for-profit sector, that operate without receiving federal financial aid (e.g., Cellini & Goldin, 2014) and are outside the scope of this chapter due to a lack of available data. As an industry, American higher education directly produces approximately $700 billion in expenditures, enrolls nearly 25 million students, and has approximately three million employees. In the following section, we discuss key revenue and expenditure categories and the implications for institutional finances.

a. Revenue

Table 1 highlights key revenue categories by institutional sector from the most recent year comprehensive data (Integrated Postsecondary Education Data System, or IPEDS) is available, the 2021-22 academic year. Due to both the business cycle and pandemic, this year is not necessarily representative of a "typical" year in each category, e.g., investment revenue. We discuss each revenue category individually in this section, as well as provide historical trends to put the 2021-2022 figures into perspective.

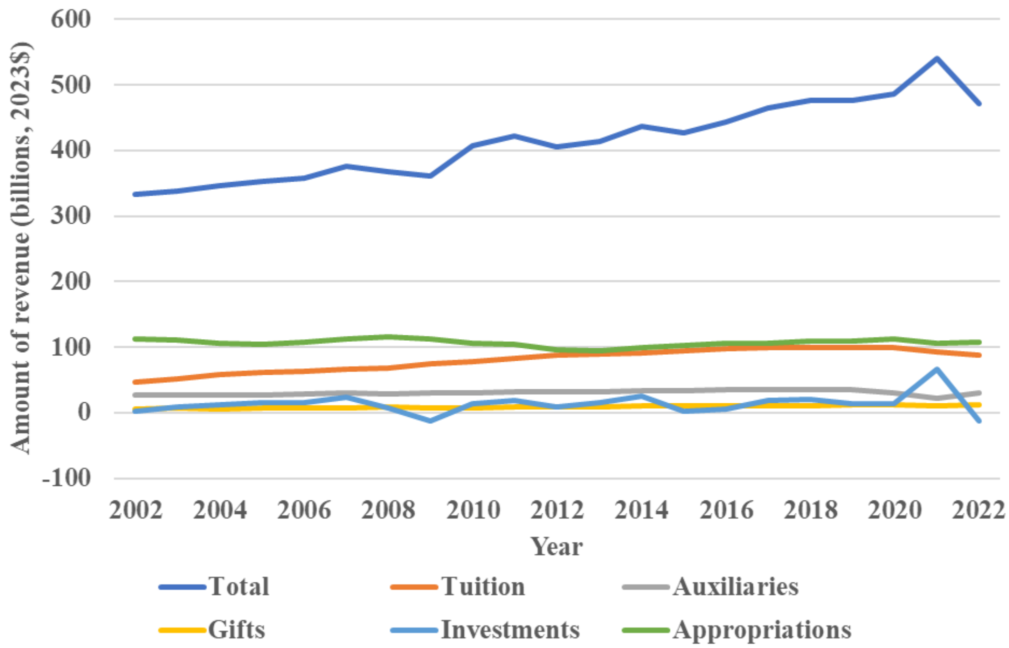
Table 1: Revenues by Institutional Sector, 2021-2022

	Public		Private nonprofit		Private forprofit	
	$	**%**	**$**	**%**	**$**	**%**
Total revenue	**460.97**	**100.0**	**220.42**	**100.0**	**18.06**	**100.0**
Tuition and fees	79.84	17.3	81.62	37.0	16.66	92.3
Appropriations	102.17	22.2	1.36	0.6	0.03	0.2
Grants and contracts	66.27	14.4	39.75	18.0	0.40	2.2
Auxiliary enterprises	28.00	6.1	17.91	8.1	0.11	0.6
Hospitals	66.86	14.5	39.43	17.9	0.00	0.0
Investment revenue	-11.32	-2.5	-26.40	-12.0	0.04	0.2
Gifts	11.66	2.5	26.40	12.0	0.00	0.0
Other	117.48	25.5	40.36	18.3	0.82	4.5

Source: IPEDS Data Explorer, Table 5, 2021-2022
Notes: Values are in billions of dollars. Approximately $15 billion in revenues from 17 FASB-reporting public institutions is excluded from this table.

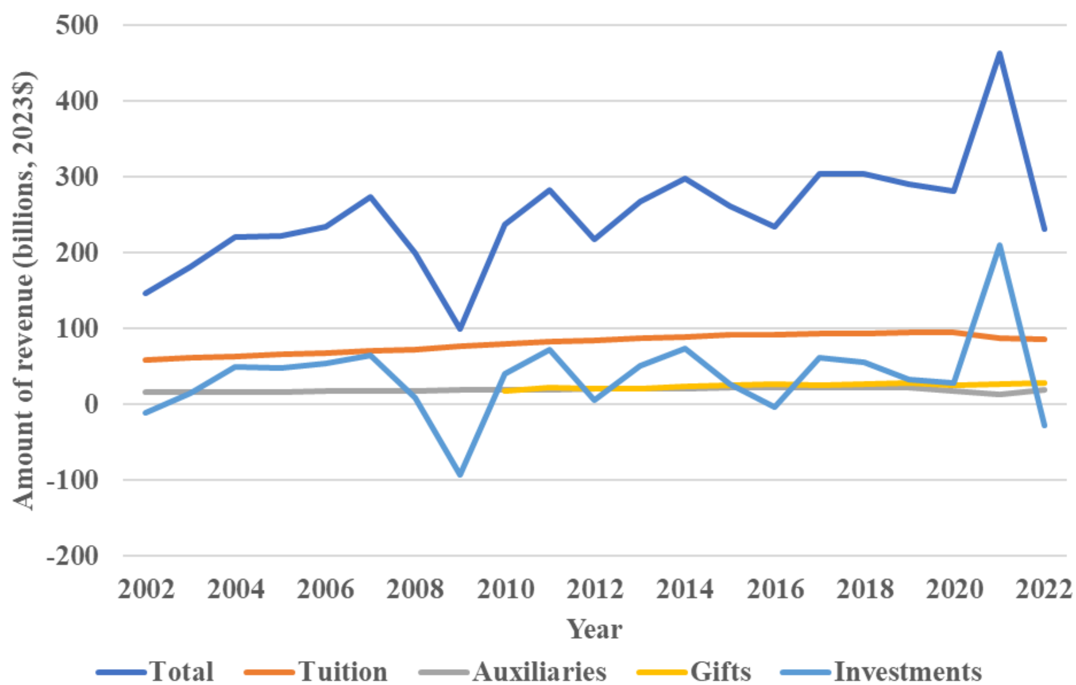
Figures 1a-1c depicts trends in key revenue categories by institutional sector between 2002 and 2022. **Figure 1a** considers public colleges and universities and shows a clear upward trend in inflation-adjusted revenue, with the total increasing from $333 billion in 2002 to $472 billion in 2022. Revenue from tuition, auxiliaries, and gifts steadily increased during most of the panel. However, revenue from both tuition and auxiliaries declined in real terms beginning in 2020 due to the coronavirus pandemic and enrollment declines. Investment revenue is generally a modest portion of total revenue and is highly dependent on stock market performance, while appropriations dipped following the Great Recession before recovering.

Figure 1a: Trends in Sources of College Revenues, Public Institutions, 2002-2022



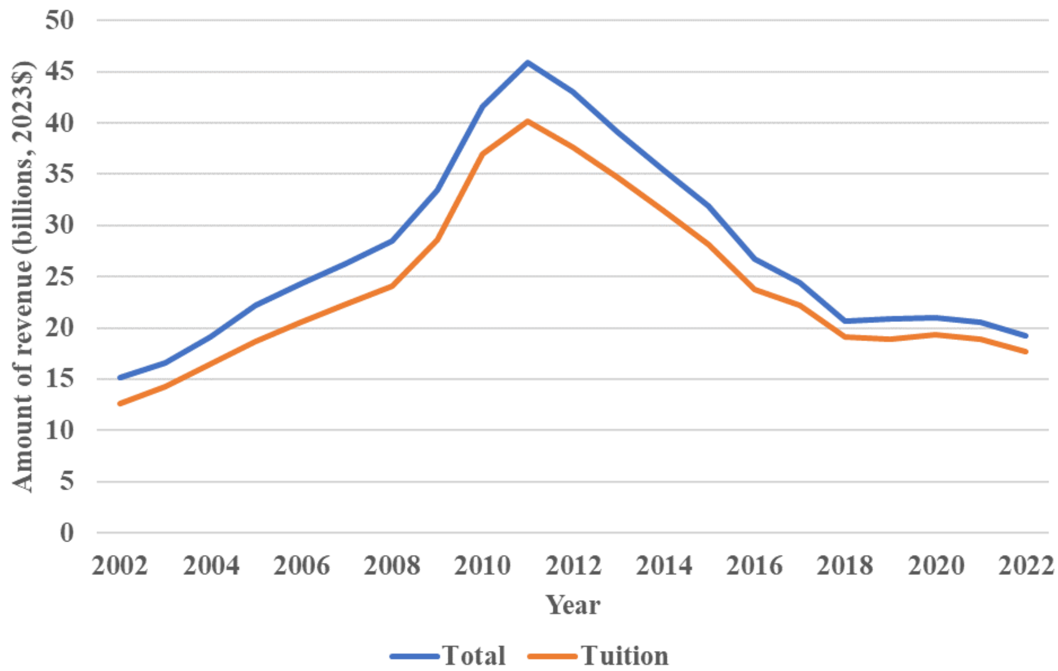
Source: Authors' calculations based on IPEDS, 2002-2022

Figure 1b: Trends in Sources of College Revenues, Private Non-profit Institutions, 2002-2022



Source: Authors' calculations based on IPEDS, 2002-2022

Figure 1c: Trends in Sources of College Revenues, Private For-profit Institutions, 2002-2022



Source: Authors' calculations based on IPEDS, 2002-2022

Figure 1b is for private nonprofit colleges, with gift revenue only being available separate from grants and contracts beginning in 2010. Total revenue in this sector over time has been highly dependent on investment returns, with real revenue falling by half between 2008 and 2009 and again between 2021 and 2022. However, the long-term trend has been toward increased revenues for the sector. Other variables have been more consistent, with tuition and auxiliary revenue generally following the same path as public institutions. Gift revenue is about twice as high compared to public colleges, while investment returns are far more influential due to a relatively small number of colleges with massive endowments.

Finally, **Figure 1c** shows two key trends about the finances of for-profit colleges. The first is that for-profit colleges have consistently derived approximately ninety percent of their funding from tuition and fees over the past two decades. Second, revenue tripled from $15 billion to $46 billion between 2002 and 2011 as the for-profit sector drew dramatically. Following enrollment declines and the collapse of some large for-profit chains, total revenue fell to just over $20 billion by 2018.

Tuition Revenue

The most important revenue source for private nonprofit and for-profit colleges, and the second most important primary revenue source for public colleges, is revenue from tuition and fees.

Between the early 1970s and mid-2010s, listed real tuition and fee rates more than tripled at public and private nonprofit colleges as strong demand for higher education allowed colleges to continue increasing their prices. But since 2018, tuition increases have consistently been below the rate of inflation (Ma & Pender, 2023) and tuition discount rates have continued to rise (National Association of College and University Business Officers, 2023), contrary to public perception of skyrocketing college costs.

Public universities can face particularly challenging situations because a majority of states explicitly restrict how much institutions can increase tuition (Kelchen & Pingel, 2024), and legislatures and governors can pressure colleges to limit tuition increases even without a formal tuition control mechanism being in place (Kelchen, 2018). This has led public universities to prioritize recruiting and enrolling out-of-state students (Jaquette & Curs, 2015), although these efforts often fail to generate additional revenue for colleges (Kelchen, 2021). At selective public universities, these efforts to recruit out-of-state students have crowded out in-state students—particularly underrepresented minority students (Curs & Jaquette, 2017; Jaquette et al., 2016).

Government Appropriations

The single most important source of revenues for public institutions is appropriations, which primarily consists of local and state funding to support general operations. At least some community colleges in nearly 30 states receive local funding, which makes up roughly 21% of total revenue for community colleges in those states (Ortagus et al., 2022). State support for public higher education is much larger (approximately $106 billion in Fiscal Year 2022 compared with $12 billion in local funding) and is spread across two-year and four-year institutions (Kunkle & Laderman, 2023). There is a strong relationship between state funding and improved completion rates and post-college outcomes alike (Chakrabarti et al., 2020).

State funding for public higher education is highly volatile, with implications both for students and colleges (Delaney, 2023). Much of this volatility is driven by higher education's function as a balancing wheel in state budgets (Delaney & Doyle, 2018; Hovey, 1999), as states make sharp cuts in appropriations during recessions in order to fund other priorities that do not have alternative revenue sources such as tuition. This leaves public colleges, particularly those that have been heavily reliant on state funding, particularly vulnerable to declines in resources and tuition increases as enrollment increases during recessionary periods of reduced state funding (Barr & Turner, 2013; Rosinger et al., 2022a). Research by Webber (2017) has also shown a relationship between state funding cuts and tuition increases, although tuition increases only backfill a portion of lost appropriations.

States allocate approximately 90% of support for public higher education to institutions, with financial aid to students—a category that is rapidly growing—making up the remainder of support (Kunkle & Laderman, 2023). States use a variety of methods to allocate funding to institutions. These include no clear funding mechanism (particularly in the four-year sector), base-adjusted methods that tie current funding to the previous year's funding, enrollment and/or performance-based models, and hybrid models that combine enrollment and/or performance components with protected base funding (Kelchen et al., 2023).

Most of the research on higher education funding models has focused on performance funding, which accounts for roughly ten percent of state appropriations (Rosinger et al., 2022b). This research generally fails to find meaningful positive effects of performance funding on student outcomes along with the presence of unintended consequences for equity (Ortagus et al., 2020); research on the effects of other funding models also comes to a similar set of muted finding (Kelchen et al., 2024a).

Research and Hospital Revenue

For a relatively small number of large public and private nonprofit universities, research (represented primarily through grants and contracts) and hospitals make up a majority of total revenue reported to the U.S. Department of Education. An example of this is the University of Michigan at Ann Arbor, which generated $5.6 billion in hospital revenue and $1.3 billion in grants and contracts in Fiscal Year 2022 compared with $1.4 billion in tuition revenue (authors' calculations using IPEDS data). Only 89 universities contributed to the nearly $67 billion in hospital revenue, as not all university-connected hospitals report financials in conjunction with universities.

Research funding is distributed across a larger group of institutions, although the vast majority of dollars flows to the 146 institutions that are designated as Research I universities in the Carnegie classifications. Research grants and contracts frequently come with indirect cost allowances that help to fund the infrastructures of personnel and facilities that are needed to support a research enterprise. These indirect cost rates tend to be higher for grants received from federal agencies compared with nonprofit foundations, creating strong pressures to seek federal research funds (Graddy-Reed et al., 2021).

Auxiliary Enterprise Revenue

Auxiliary enterprises consist of activities that are not directly tied to instruction, research, and student services. Some of these activities, such as housing, food service, and parking, are typically expected to break even or potentially help support other campus activities through generating a profit. Other activities, such as athletics, may be allowed to operate at a loss in order to help achieve other institutional priorities. Auxiliary revenues reflect a modest share of overall revenue across higher education, but are particularly important at residential liberal arts colleges and large research universities with sizable on-campus populations and prominent intercollegiate athletics programs.

Because housing, dining, and parking generate consistent revenue streams, a growing number of public universities have sought capital to upgrade their facilities in these areas. This can take the form of issuing bonds to finance improvements (Denison et al., 2014) or through using public-private partnerships that leverage private capital to make improvements and then lease the assets back to universities (McClure et al., 2017; Storms et al., 2017). Private universities typically issue bonds on their own, which helps to explain higher debt burdens among private than public institutions because some debt associated with public universities is held outside of balance sheets (Ward et al., 2022).

The vast majority of revenue from intercollegiate athletics comes from the approximately 360 universities in Division I of the National Collegiate Athletic Association (NCAA), and much of this revenue is concentrated among the approximately 60 institutions in the most powerful athletic conferences. Forty-nine public universities brought in more than $100 million in athletics revenues in the 2021-22 fiscal year (USA Today, 2024), but many Division I institutions still rely on student fees and institutional contributions in order to fund athletics. Total student fees for athletics are in excess of $1 billion per year and can exceed $2,000 per student per year at some universities (Enright et al., 2020). Meanwhile, smaller institutions view athletics as a way to recruit tuition-paying students who want to continue their athletic careers and thus are willing to operate athletics with little direct revenue (Knox, 2023).

Investment and Gift Revenue

Like research and hospital revenue, the vast majority of support from private donors is concentrated in a small number of colleges. Just 136 colleges or university systems in the United States had endowments of more than $1 billion in Fiscal Year 2023, but they account for more than 80% of all endowment assets in American higher education. Going further, five institutions held 25% of all endowment assets and 25 institutions held half of all assets (Redd, 2024). Private institutions are far more reliant on endowments and investment income than public institutions, as private institutions hold the majority of assets and tend to have smaller student bodies to support (Baum et al., 2018).

A college's endowment does not consist of one single piggy bank that leaders can use in any way they see fit. Rather, endowments are made up of numerous accounts that frequently have restrictions placed on their usage by donors. Common categories for giving include student financial aid, funding the building and maintenance of facilities, and supporting faculty positions. Institutional leadership can petition a court to remove restrictions in the case of financial distress (e.g., Moody, 2024), but those efforts tend to be expensive to undertake and can damage relationships with donors. In general, colleges are expected to spend approximately 4% to 5% of a rolling average value of the endowment each year. This is below the long-term rate of return, which allows endowments to keep growing (American Council on Education, 2014). It also helps to smooth out year-over-year changes in the value of the endowment, which have been considerable over the last decade.

b. Expenditures

One of the key challenges facing colleges and universities is that operating costs have increased faster than general inflation for decades, driven by rising expenses for health insurance and administrative support (Commonfund Institute, 2023). To provide an extreme example of rising costs, the University of Delaware announced in early 2024 a freeze on all nonessential spending in large part due to skyrocketing health insurance costs driven by the popular weight loss drug Ozempic (Greene, 2024; Owens, 2024). This is a particular concern for public institutions, which often have limited control over benefits costs compared with private institutions.

Postsecondary education suffers from Baumol's (1967) cost disease as an industry that relies on highly educated labor and is unable to incorporate technological efficiencies as well as many other fields; this has explained the majority of rising operating costs over time (Archibald & Feldman, 2008). However, Bowen's rule, in which colleges seek to raise as much money as possible in order to spend it on educationally worthwhile pursuits, likely also plays a role in rising expenditures as institutions try to keep up with their peers (Bowen, 1980; Kolpin & Stater, 2024).

As a labor-intensive industry, expenses related to personnel are by far the single largest expenditure category in most institutions' budgets. While the share of faculty who are tenured or are on the tenure track has steadily declined over time (Colby, 2023), even a move to contingent faculty does not eliminate the need for individuals to teach classes. The two other primary drivers of institutional expenses are maintaining facilities and debt service. Both of these categories also tend to be difficult to change in the short or medium term, as there is often little ability to sell off assets that are on an existing college campus and bonds are often paid off over a period of several decades. As a result, it is difficult for colleges to make meaningful reductions to budgets without eliminating a broad range of academic programs.

Table 2 highlights key functional expenses by institutional sector in the 2021-22 academic year. More money was spent on instruction than any single other category across both public and private nonprofit institutions, but this only included between 26% and 30% of all spending. This low share of spending on instruction often raises concerns regarding so-called administrative bloat, which is a rare argument that unites faculty members with advocates from across the ideological spectrum (e.g., American Council of Trustees and Alumni, 2021; Ginsberg, 2011; Whistle & Erickson, 2019).

Table 2: Expenses by Institutional Sector, 2021-22

	Public		**Private nonprofit**		**Private for-profit**	
	$	**%**	**$**	**%**	**$**	**%**
Total expenses	**439.79**	**100.0**	**246.08**	**100.0**	**15.80**	**100.0**
Instruction	116.14	26.4	68.48	27.8	4.77	30.2
Research	44.64	10.2	26.66	10.8	0.01	0.1
Academic support	34.49	7.8	20.84	8.5	1.54	9.7
Student services	24.00	5.5	21.14	8.6	3.07	19.4
Institutional support	40.93	9.3	30.51	12.4	4.99	31.6
Auxiliary enterprises	33.51	7.6	18.18	7.4	0.22	1.4
Hospitals	64.33	14.6	39.81	16.2	0.00	0.0
Other	81.74	18.6	20.45	8.3	1.21	7.7

Source: IPEDS Data Explorer, Table 5, 2021-2022
Notes: Values are in billions of dollars. Approximately $15 billion in expenditures from 17 FASB-reporting public institutions is excluded from this table.

The construction of the instructional expenditures category in IPEDS is relatively narrow, excluding key functions such as advising, information technology, and student support services. These three categories represent just under one-fourth of all spending at public institutions, but 60% of spending at for-profit colleges. Research has shown that spending in these areas has been shown to significantly improve student outcomes (Griffith & Rask, 2016; Webber & Ehrenberg, 2010). Spending on other categories, such as research, auxiliary enterprises, and hospitals tends to be more closely aligned with the associated revenue categories and is less driven by tuition dollars and state appropriations.

III. Data Sources

A. Institutional Characteristics (IPEDS and College Scorecard)

We obtain information on the historical features of colleges and universities (organizational structure, location, and finances) and on the characteristics of their students and staff primarily from the Department of Education's Integrated Postsecondary Education Data System (IPEDS) data. The panel we assemble spans from 2002 to 2022 and is based on data which is collected annually on the academic year calendar for each UnitID (IPEDS ID for an individual institution). Some of the IPEDS data we collect are available prior to 2002, but data elements collected frequently changed during the 1990s and are missing for a large share of institutions either because the institution's sector was not asked a particular module or because reporting was optional for the type of institution in a particular year. We focus on institutions in the 50 states and Washington, DC in this analysis.

We use the predominant degree from the College Scorecard and IPEDS to classify institutions into public 2-year (or less), public 4-year (or more), private non-profit 2-year (or less), private non-profit 4-year (or more), private for-profit 2-year (or less), and private for-profit 4-year (or more). Considering the predominant degree classification better reflects the institutions' focus, since highest degree offered would often classify community colleges that offer a single, small B.A. program as "4-year" institutions. About a fifth of colleges are missing information on the predominant degree level variable, so we supplement with Carnegie classifications where available and counted the rest as two-year colleges (confirmed by visual inspection of the data for missing predominant degree level).

The rich IPEDS data include hundreds of variables, with many of them only available for certain institution types or enrollment/revenue thresholds. We consider a range of variables that could potentially be associated with college closures based on prior research, economic theory, and our experiences in the field of higher education finance. The main variables drawn from IPEDS that are of focus for this study include:

- Enrollment: total enrollment; change in enrollment; share full-time enrollment; share undergraduate enrollment
- Staff: total staff; change in staff; share full-time staff; share instructional staff

- Revenues: total revenue; change in revenue; shares of revenue from tuition, auxiliary enterprises, investments, and gifts/grants/contracts
- Expenses: total expenses; percent change in expenses; shares of expenses on instruction, scholarships, interest, depreciation, and salaries
- Assets and debt: Unrestricted net assets; debt; endowment
- Derived financial metrics: operating margin; change in operating margin; days cash on hand (liquidity); change in days cash on hand; earnings before debt, interest, and amortization (EBIDA); debt to EBIDA; debt to assets (leverage); change in debt to assets
- Other derived measures: ten percent decline in revenue relative to high in the last five years; persistent negative operating margin (at least three of the past five years); ten percent decline in enrollment relative to high in the last five years; five percent or more decline in enrollment each year for the last three years

We adjust financial values such as total revenue, assets, and debt into 2023 dollars using the Consumer Price Index but leave year-over-year percent change metrics as nominal values. For variables with skewed distributions in our analyses (generally, dollar values and measure of students/staff counts), we use logs of nominal values, and Winsorize outliers at the 2.5 percent level.

As mentioned previously, most data fields have considerable coverage. That said, data are missing for a variety of reasons, both idiosyncratic and systematic. For example, institutions that only grant certificates frequently do not report detailed asset or other financial data. Given the low risk of bias due to a correlation between the (systematically) missing values and likelihood of closure after conditioning on covariates such as sector or degree level, we include indicators for reasons data is missing (e.g., institution type such that detailed financial data is unavailable) in certain models in order to maximize sample size; we discuss this process in more detail in the next section. The variables most susceptible to missing values are virtually all measures of debt, assets, and leverage.

In addition to the enumerated variables, the IPEDS data contain a wealth of institutional, financial, student, and staff fields that we consider potentially marginally informative for purposes of predicting financial distress of institutions of higher education. When possible, we assess how much incremental explanatory value these metrics hold, but the covariates selected above are expected to be and empirically are the relatively stronger predictors,

B. College Closures (PEPS)

To consider college closures in the context of this study, we draw on the Closed School Weekly Reports from the Federal Student Aid's (FSA's) Postsecondary Education Participants System (PEPS) database. FSA data classify institutions based on their Office of Postsecondary Education identification number (OPEID), which is based on the unit of analysis under which a program participation agreement is entered upon with the Department of Education (Office of Federal Student Aid, 2017). We restrict the sample of institutions in the PEPS data to those where the main campus (FSA OPEID ending in "00"), as opposed to a branch/satellite campus, closed.[1] We made this decision because colleges frequently close branch campuses that may only offer one or two programs of study; fully 90% of closures in PEPS in the 2010s were of branch campuses.[2] The PEPS data includes a precise date of closure as reported by the U.S. Department of Education, which can be months or even years after the closure was initially announced. A small number of colleges closed, reopened, and then closed again during the period of analysis, but we considered the first closure only in our analyses. PEPS data as of the writing of this paper were only available through November 2023, so 2023 is an incomplete year of data.

Combining data at the IPEDS UnitID and FSA OPEID levels is a complex endeavor as there the relationship between the two classifications is not one-to-one. College and university systems often operate under the same program participation agreement with the FSA, and thus all report data together under what is often called a "parent-child" agreement (Jaquette & Parra, 2014). However, seemingly similar university systems differ in whether institutions report separately or jointly to FSA. For example, Indiana University and University of Wisconsin campuses report separately, while Ohio State University and Rutgers University report as systems. Further complicating this data merge is that colleges that share the same program participation agreement can report certain IPEDS data elements (such as finance and completions) at the OPEID level while reporting other elements (such as enrollment and staffing) at the UnitID level (National Center for Education Statistics, 2018).

[1] Some colleges have hundreds of branches listed in PEPS, and PEPS creates a new OPEID by adding 10, 20, 30, or 40 to the original OPEID. In about ten cases, this new OPEID had a branch campus ending in 00, but we dropped those observations because they are not main campuses. An example is OPEID 10224300, which is Central Michigan University's former branch campus at Schoolcraft College.

[2] An example of this is Georgia's Piedmont College, which closed 32 branch campuses in 2020 alone. All of these campuses were in local school buildings. A similar dynamic occurred at Oregon's Concordia University, which closed its main campus in 2020. However, it closed multiple branch campuses in area school buildings in 2014, which was near the peak of its enrollment and years before any financial challenges. Additionally, there are no data available on the size of these branch campuses or their financial characteristics.

We meticulously aggregate all of our data to the OPEID level to reduce this complication, although it comes at the expense of focusing on only main campus closures. If there were two-year and four-year institutions within the same OPEID, we consider the resulting overall institution to be a four-year college. This results in a final sample of 8,633 institutions that operated and were eligible to receive federal financial aid at some point during the panel; more than one in ten closed during our sample period, as we will show below. We were unable to match 55 closures in the PEPS data to IPEDS UnitIDs, with all but nine of those non-matches occurring between 1996 and 1998. These relatively few institutions are therefore excluded from our analyses.

C. Federal Accountability Metrics and County Characteristics

To flag institutions perceived by sector observers to be in precarious financial condition, we use the College Scorecard data on colleges placed on Heightened Cash Monitoring (HCM) level 2, the most serious level of federal monitoring that requires a college to get reimbursed after the fact for federal financial aid disbursed to students instead of receiving those funds in advance. In other words, HCM2 places scrutiny on each student's aid package to minimize risk of lost funds to taxpayers (Office of Federal Student Aid, 2019). We also use data from Federal Student Aid on whether private colleges failed the government's Financial Responsibility Composite (FRC) score, which places colleges on HCM level 1.

Cohort default rates (CDRs) are another accountability tool available to the federal government and represent the share of an institution's student loan borrowers who are in default. Historically, CDRs have tended to flag many low-value programs (especially in the private sector) somewhat accurately, but retain relatively less value from a prediction perspective going forward. This is due to the availability of increasingly generous reduced payment plans (including automatic enrollment in case of 90+ days late payments) and debt cancellation available to federal student loan borrowers. These recent policy changes are likely to dramatically reduce default rates to a point where they are no longer information. Although we collected CDR data, we exclude this metric from our analyses given that the most likely context for a real-life application of our methodology is predictions of future college financial distress based on most recent data.

We also collect measures of population and income per capita received by local residents at the county level, from 1967 to 2022, from the U.S. Bureau of Economic Analysis. Finally, we collect estimates of the poverty rate at the county level from the Small Area Income and Poverty Estimates survey from the U.S. Census Bureau for 1997 - 2022. The county-level unemployment rate is obtained from the Bureau of Labor Statistics' Local Area Unemployment Statistics program for 1990 - 2022.

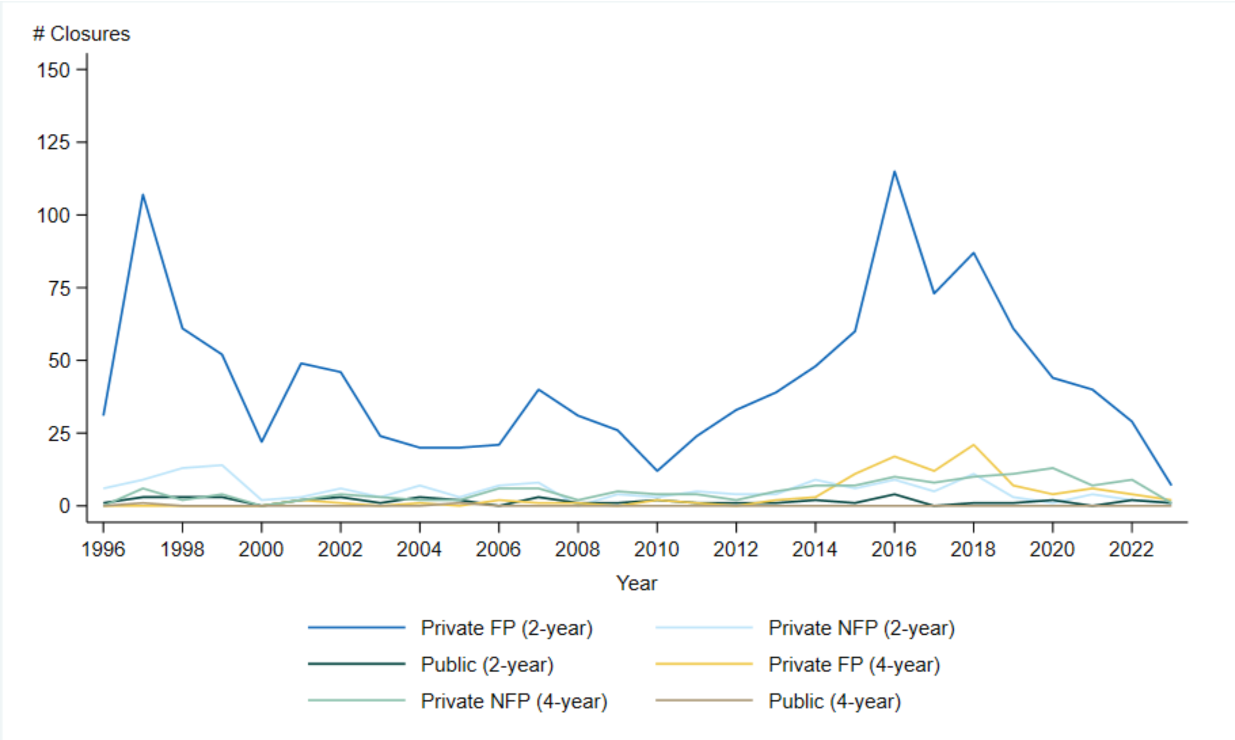
D. Analytical Sample – Closure Predictions

Appendix Table A1 shows summary statistics of the analytic panel, divided between observations with closed colleges (using data from two years prior to closure) and observations for colleges that never closed during our sample period of 2002-2023. Colleges that closed were smaller, more tuition-driven, and saw larger declines in enrollment and revenue than colleges that remained open. For example, more than one-fourth of colleges that closed posted operating losses in at least three of the five years prior to closure. This was twice the rate of colleges that remained open. However, there is a substantial overlap in the distributions of variables between open and closed colleges, highlighting the need for multivariate predictions.

Figure 2 highlights the number of colleges that closed in each year between 1996 and 2023, broken down by institutional type and level based on the predominant degree offered. As the previous literature shows, the majority of institutions that closed were for-profit 2-year colleges with relatively few students. **Table 3** shows the number of colleges that ever existed and/or closed during our panel by institutional type and level. Overall, a total of 1,671 colleges closed during the period of analysis, with the number of closures peaking between 2016 and 2018.

A striking fact emerges from our data: public institutions hardly ever close. Only two four-year public institutions (one tribal college and one graduate health sciences-focused institution) closed during the panel, and nearly all of the 45 two-year public institutions that closed were career and technical centers run by local school districts. This shows that despite challenging operational metrics, public institutions under financial pressure tend to remain open, particularly if there is a dearth of public education options in the local area. If more drastic measures are required in order to address financial distress among public institutions, more often than not it will be mergers or consolidations that are presented as the remedy, and not closure. This is in part because closing a public college is a deeply political decision, similar to closing military bases. As a result, less drastic steps are typically taken that preserve an educational option in the local community. In future work, we hope to collect data on these mergers and consolidations, but they are not available for the present study. As a result, we focus our closure-related analyses on private institutions; however, we consider public institutions when estimating the likelihood of facing significant financial distress.

Figure 2 – Number of Closed Institutions by Institution Type and Year, 1996-2023



Source: Authors' calculations based on PEPS Closed School Reports, 1996-2023

The vast majority of closures have been among private for-profit colleges, which is intuitive because for-profit colleges are much more likely to exit the marketplace if they do not see the opportunity to make a profit in the future. They are, as Deming et al. (2012) famously posed, nimble critters. Nearly three-fourths of closures in the dataset are two-year for-profit colleges, and almost one-third of the 3,732 institutions observed in this sector closed at some point between 1996 and 2023. On the other hand, while private nonprofit four-year colleges get the lion's share of attention regarding college closures, closure rates are relatively modest (just over seven percent during this time period).

Table 3: Number of Institutions that Ever Closed, by Institution Type, 1996-2023

Sector	Number of institutions	Number of closures	Closure rate
Public 4-year	850	2	0.2%
Public 2-year	1,682	45	2.7%
For-profit 4-year	473	100	21.1%
For-profit 2-year	3,732	1,222	32.7%
Nonprofit 4-year	2,002	142	7.1%
Nonprofit 2-year	732	152	20.8%
Total	**8,633**	**1,661**	**19.2%**

Source: Authors' calculations based on PEPS Closed School Reports, 1996-2023

Note: A small number of colleges changed sectors during the panel, and they are reported in both sectors.

Table 4 shows the share of colleges in operation by sector in 1996 that were still in operation in 2006, 2016, and 2023, as this highlights the longevity (or lack thereof) of colleges that were in the panel in the very beginning. Nearly 40% of the two-year for-profit colleges open in 1996 closed by 2023, with many of them closing in the late 1990s. Most of the closures among four-year for-profits closed in the 2010s and early 2020s, while closures in the nonprofit sector were relatively more evenly distributed over time.

Table 4: Trends in Closures by Institution Type Among Colleges Open in 1996

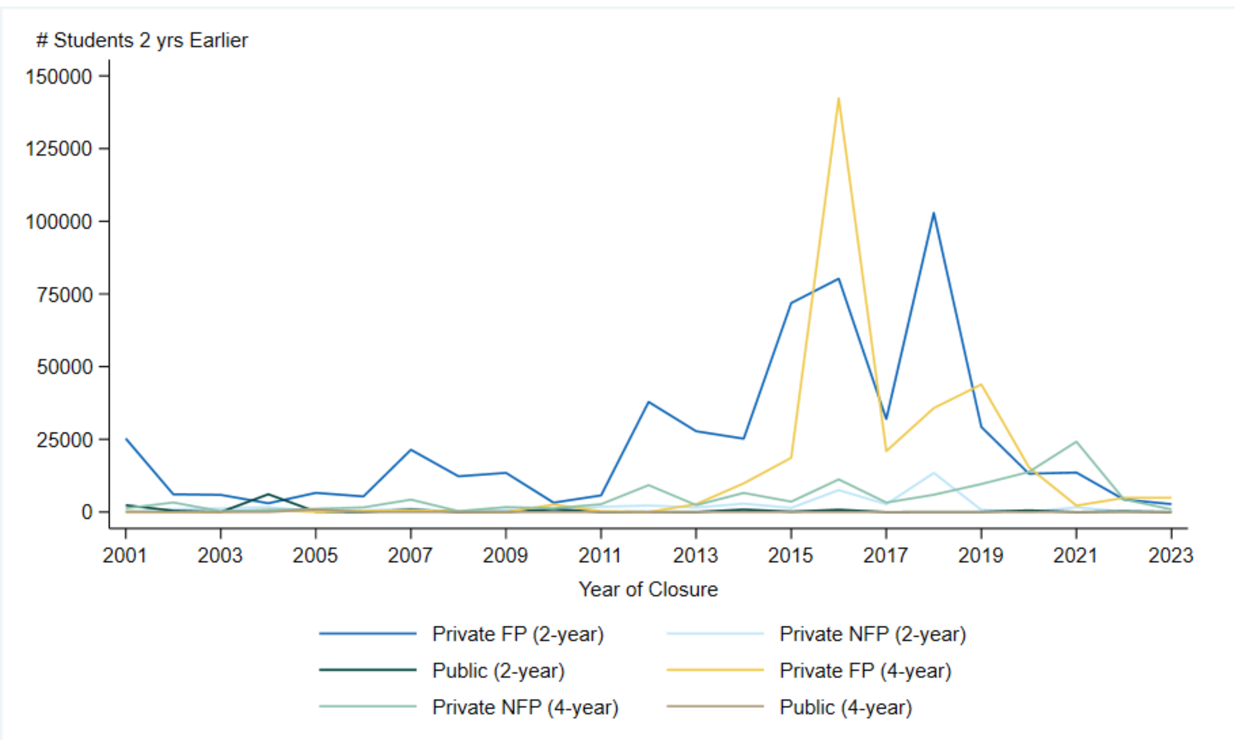
Sector	Open in 1996	Closed by 2006	Closed by 2016	Closed by 2023
Public 4-year	778	0.3%	0.3%	0.3%
Public 2-year	1,389	1.1%	1.6%	1.9%
For-profit 4-year	332	1.8%	10.8%	24.1%
For-profit 2-year	2,339	17.5%	29.4%	38.3%
Nonprofit 4-year	1,715	1.7%	4.3%	7.3%
Nonprofit 2-year	548	10.9%	18.1%	21.2%
Total	**6,411**	**8.1%**	**12.7%**	**19.4%**

Source: Authors' calculations based on IPEDS and PEPS Closed School Reports, 1996-2023

Note: A small number of colleges changed sectors during the panel, and they are reported in both sectors.

Figure 3 shows the number of students affected by college closures each year between 2001 and 2023 by institution classification. Median full-time equivalent (FTE) enrollment two years prior to closure (for example, 2017-18 enrollment for a 2019 closure) was 219 students at nonprofit colleges and 162 students at for-profit colleges. Most colleges in the sample were small, with median enrollment among nonprofit colleges being 1,015 students and just 192 students at for-profit colleges, such that closed schools are somewhat smaller than average (but not dramatically so). However, a few prominent closures in the for-profit sector (such as the Art Institutes and ITT Tech) resulted in just over one million students during our panel who attended colleges that closed two years later. The vast majority of students affected by closures were in the 2010s.

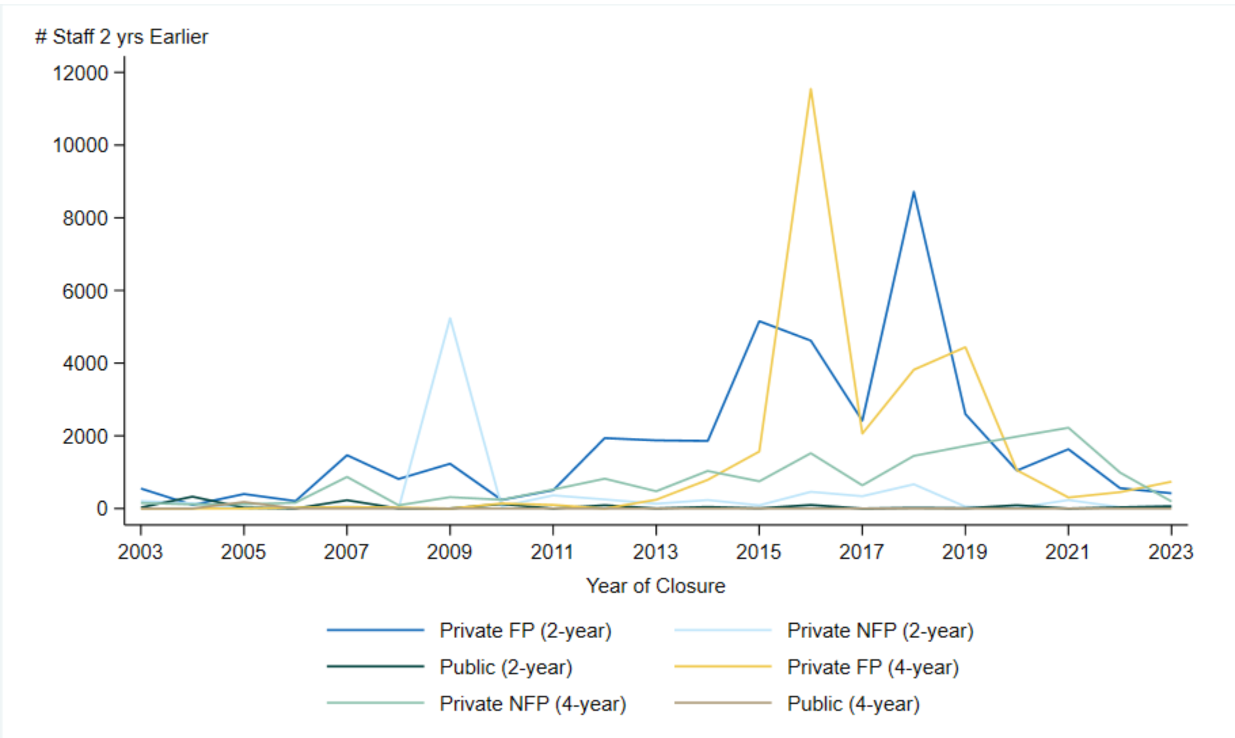
Figure 3 – Number of Students Enrolled in Closed Institutions Two Years Prior to Closure, by Institution Type and Year, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2001-2023

Figure 4 plots the number of staff affected by college closures each year by institution classification, again using staff data from two years prior to the closure date. Again, the vast majority of colleges that closed had relatively few employees. The median for-profit college that closed had 20 employees, compared with 48 employees at the typical private nonprofit college. Yet there were approximately 100,000 employees across all affected institutions between 2003 and 2023, with about 70% of affected employees working at for-profit colleges. Just over 200 closures had more than 100 employees, reflecting a potentially sizable impact on the local economy.

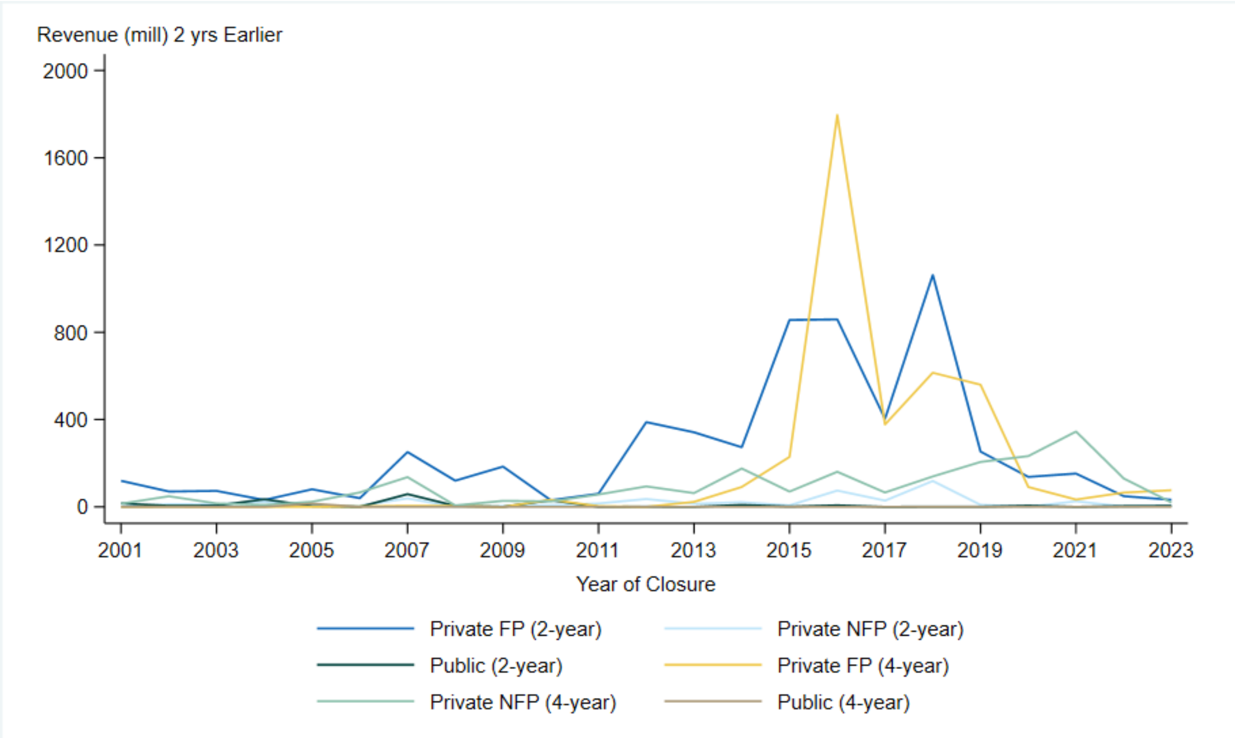
Figure 4 – Number of Staff Employed by Closed Institutions Two Years Prior to Closure, by Institution Type and Year, 2003-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2003-2023

Finally, **Figure 5** examines the total revenue generated by institutions that closed two years later. The median total revenue was $2.18 million two years prior to closure, with the median nonprofit college having total revenue of $5.06 million and the median for-profit college having total revenue of $1.84 million. Nearly one-fifth of all closed colleges generated at least $10 million in revenue two years before closing, and the total amount of revenue generated by closing colleges exceeded $13 billion over the last two decades. Again, the large for-profit college closures explain the substantial revenue values in the mid-to-late 2010s.

Figure 5 – Total Revenue at Closed Institutions Two Years Prior to Closure, by Institution Type and Year, 2003-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2001-2023.

IV. Methodology

A. *Identifying Predictors of Financial Distress*

We build on the analysis in Kelchen (2020), which examined the extent to which institutional and local economic conditions two years or four years earlier were associated with a college closing in a given year. We begin by implementing a supervised machine learning classification algorithm using a distributed gradient boosting decision tree methodology, and specifically the XGBoost algorithm (Chen and Guestrin, 2016). We do this in order to make the most out of the rich data we have assembled and because the IPEDS data that forms the basis of our panel exhibits considerable gaps. Since classification algorithms such as XGBoost are designed to handle large amounts of flawed data and because they consider complex interactions and nonlinear relationships, they are likely to be better suited for predicting rare events like college closures or financial distress compared with traditional linear probability estimation and with extant score-based accountability metrics.[3] XGBoost is particularly well suited for predictive analytics and builds upon traditional gradient boosting methods while introducing several enhancements that make it particularly efficient and tractable compared with other machine learning algorithms.

We then compare the performances of the XGBoost algorithm to several alternative models. First, we estimate a linear probability model using continuous controls consistent with the equation:

$$Y_{it} = \alpha + \beta X_{i,t-2} + \gamma X_{i,t-n} \ldots + \delta W_i \ldots + \theta_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is an outcome variable denoting either closure or a measure of financial distress (ten percent enrollment decline relative to 5-year high, 10 percent revenue decline relative to 5-year high, 3 consecutive years of a negative operating margin, or Heightened Cash Monitoring Level 2 status) as of time t. $X_{i,t-n}$ represent lags of varying lengths of time-varying institutional characteristics (e.g., revenue, enrollment), W_i represents time-invariant institutional characteristics (e.g., sector or predominant degree level), and θ_t represents year fixed effects.

In an attempt to increase the number of colleges for which we can generate predicted probabilities (in other words, to increase the sample size), we produce a series of least absolute shrinkage and selection operator (LASSO) estimates for each of our outcome variables as part of a data-driven covariate selection process. The LASSO procedure allows us to focus our attention on the set of covariates that produces the smallest out-of-sample mean squared error of the predictions, which allows us to reduce the dimensionality of the prediction problem while simultaneously identifying the strongest predictors of financial distress for colleges. This is important given the high prevalence of missing values in our data. To put it differently, we can reduce the number of covariates in the linear probability models, which allows us to use more observations and therefore produce predictions of financial distress for more institutions. Once we identify the optimal set of covariates for our sample using the LASSO procedure, we then estimate the equation (1) using standard OLS regression.

We also estimate a linear probability model using binned versions of the continuous controls. We do so because we are necessarily restricted to the sample with non-missing covariates if we use

[3] For simplicity, much of the discussion in this section references closures, but we estimate our models for the full set of derived outcome variables enumerated previously. The modeling choices and the proposed principles for using/interpreting the model output translate for all of the other metrics of financial distress, as well.

continuous values, and because linear relationships between measures such as enrollment, staff, or revenue and the likelihood of closure are not necessarily reasonable to assume. With binned controls, we can include observations in "expected missing" bins for each covariate when the field in question is expected to be missing, for example if a particular institution type was not fielded a particular module in a given year. To put it differently, we can derive predicted closure probabilities for institution-year observations with one or more expected missing values in our sample, which is important in our setting given that some two thirds of institution-year observations have at least one expected missing value among covariates most likely to be predictive of closures. We refer to the larger sample (which includes one or more covariates with missing values for a given institution-year) as "full sample" and to the smaller sample where each covariate is populated for each institution-year as the "nonmissing sample."

For an alternate version of the XGBoost algorithm, we also include richer covariates, including additional lags of variables included in the model and a host of additional institutional characteristics that did not rise highly enough in the priority list for the limited controls (either continuous or binned) models, but might be helpful for increasing predictive accuracy for XGBoost. One of set of these additional variables includes lags of county-level covariates (poverty rate, unemployment rate, log of population, and income per capita) to ascertain whether the local economic environment might be contributing to college financial distress. Because public institutions rarely close, we restrict our sample to private colleges and universities and consider the time period between 2001 and 2023, when the majority of our preferred covariates have at least some coverage.

To compare the performance of these predictive models, we split our observations into 75% training data and 25% evaluation data, then estimate the different models on the two described samples of our training data. This results in a total of six model-data pairs which we can then compare in terms of goodness-of-fit measures (such as the area under the curve, or AUC, considering acceptable true positive rates, or TPR, and false positive rates, or FPR).[4]

[4] AUC is the area under the ROC curve, which is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various thresholds. The ROC curve compares the models' TPR and FPR to a random assignment. Higher AUC implies that the model is more successful at correctly classifying the binary outcome. An AUC of 0.5 essentially means that the model is no better than random chance, while models with AUC in excess of 0.8 or 0.9 are considered highly effective at correctly classifying the outcome.

The model-data pairs are:

A. Linear probability model using select continuous variables – non-missing sample,
B. Linear probability model with LASSO selection using select continuous variables – non-missing sample,
C. Linear probability model using select binned variables – full sample,
D. Gradient boosting algorithm using select binned variables – full sample,
E. Gradient boosting algorithm using select continuous variables – full sample, and
F. Gradient boosting algorithm using all continuous variables – full sample.

In principle, each subsequent model is able to improve upon predictive ability, either by improving accuracy conditional on sample (e.g., E → F) or by improving sample size and therefore the set of institutions for which prediction can be generated (e.g., A → B).

B. Considering Screening Models for Detecting Closures

The focus of this analysis is on predicting college closures, rather than causally identifying the effect of particular covariates on the probability of closure. For this reason, we focus much of the discussion on the predictive accuracy of the models rather than the direction or magnitude of individual coefficients. That said, we also analyze our model output to ascertain feature importance and identify covariates that contribute most to predictive accuracy, while cautioning the reader that prediction models that do not take into account causation are inherently unstable. Analysts should take care to monitor model performance carefully, especially with respect to evolution over time.

We use the predicted probabilities of closure from the models to derive metrics of predictive precision. This allows us to examine the relationship between model choice and the accuracy of closures predictions, and to consider ways in which predictions like ours can be interpreted and used for monitoring the higher education sector. This includes both the possibility of false positive and of false negative predictions when transforming predicted probabilities into binary classifiers.

The output from our models can be used in at least two commonly accepted ways. First, the predicted probabilities can be used in their continuous form to consider relative risks, including by rank-ordering institutions. The predicted probabilities serve a "distance to default" sort of purpose, similar to the FRC score calculated by the Department of Education, which may be particularly helpful in sorting institutions into "zones of danger," as well as monitoring risk of financial distress over time. They can also be used to prioritize additional data collection or examination, along the lines of Internal Revenue Service audits; an economical auditor will know to stratify their examinations, selecting higher shares of institutions with higher predicted risk and no institutions with very low predicted risk.

Second, the predictions can be translated into binary classifiers, akin to government metrics such as HCM2, meant to serve as a warning sign for institutions that could be at risk. For any such metric, there is a tradeoff between false positives (institutions included in the list that are not at risk of closure) and false negatives (institutions at risk of closure that are not placed on the list). In illustrative examples, we show how the models estimated in this paper can be used in conjunction with threshold selection methodologies in ways that perform better than currently used metrics of financial risk. To formalize this, we estimate both XGBoost and linear probability models using the two key federal accountability metrics – HCM2 and the FRC score – and compare the predictions from these models to predictions from our preferred full models with the richest controls. These estimates can serve as a useful benchmark for the predictive power of our models.

C. Simulating Changes in Closures

With a model predicting college closures in hand, we can use the estimated coefficients to simulate aggregate predicted closures under different potential fiscal paths for institutions of higher education. In other words, what types of institutions may be at risk of financial distress in the future given reasonable and extreme scenarios on enrollment, revenue, and expense trends? Still on the horizon for many schools is the so-called "demographic cliff", which might see overall higher education enrollment drop by as much as fifteen percent between 2025 and 2029. These impacts would be concentrated locally and regionally based on declines in college age populations resulting from changes in migration and fertility rate patterns, such that some institutions of higher education (e.g., those in the Northeast and Midwest) could see even larger downturns while others (e.g., those serving Hispanic students) would be largely unaffected.

To start, we use 2019 as a baseline, and estimate the change (increase) in closures suggested by our estimated coefficients for the following scenarios:

a) The enrollment declines institutions have experienced since 2019 persist into the future (with no recovery or further decline), or
b) The predicted "demographic cliff" style (e.g., Grawe, 2018) aggregate enrollment declines of 15% between 2025 and 2029 come to pass.

We make certain assumptions to approximate a more realistic scenario, since it is unlikely that enrollment would change in isolation. Instead, we assume that revenues and expenses scale with enrollment, and that institutions maintain the same revenue and expense shares when this occurs.

V. Results – Predictive Accuracy

A. Closures Predictions – Overall Accuracy

Consistent with our methodology discussion in the previous section, we estimate linear probability (including classic OLS and LASSO-informed OLS) and XGBoost models with different sets of controls: a) selected continuous covariates, selected binned covariates, and a full set of available covariates. We do so for two samples: 2002-2023 (full sample) and for 2006-2020 (sample for which federal accountability metrics are more consistently available). We define our closure outcome as "closed in year *t*"; as an alternative approach, we also create a measure of "closure" defined as "closed within 3 year of year *t*" instead of "closed in year *t*," which could represent an alternate monitoring objective. We do so because our models may perform better in predicting closures that are coming "soon" without being required to predict the specific year of those closures as well, thereby flagging an institution for risk of closure.

Again, due to missing values, sample sizes vary considerably, being by far the lowest for the linear probability models with continuous covariates and no help from LASSO. We compare AUC metrics for each of the models, samples, covariates, and outcome measures we consider in **Table 5**, below, in order to arrive at our preferred model. For all specifications other than "All Controls," we use 2-year and 3-year lags of all time-variant control variables, which we identify as the optimal number of lags based on a comparison of AUCs for models with increasingly larger numbers of lags of the same set of covariates. Once we bring in a fuller set of covariates in "All Controls," we allow up to 5 lags in the XGBoost model; the linear probability models perform quite poorly for this larger set of covariates, so we omit those results from the table.

Table 5 – Predictive Accuracy for Linear Regression and XGBoost Models, 2002-2023

Sample	Model	Controls	Closure (point in time)			Closure (within 3 yrs)		
			Predicted Closures	AUC	Sample Size	Predicted Closures	AUC	Sample Size
2002-2023	Linear Probability	Select Continuous	11	74.5%	2,624	39	81.1%	2,624
	Linear Probability - LASSO	Select Continuous	32	78.7%	2,973	75	84.1%	2,973
	Linear Probability	Select Binned	287	75.8%	15,568	1,036	78.8%	15,568
	XGBoost	Select Binned	284	79.7%	19,762	1,110	82.2%	19,762
	XGBoost	Select Continuous	270	80.9%	19,762	1,087	83.4%	19,762
	XGBoost	All	246	82.3%	19,762	1,066	86.4%	19,762
2006-2020	Linear Probability	Federal Metrics	167	78.1%	10,404	615	77.7%	10,404
	XGBoost	Federal Metrics	261	79.3%	15,966	1,000	79.3%	15,966
	Linear Probability	Select Continuous	11	74.5%	2,624	39	81.1%	2,624
	Linear Probability - LASSO	Select Continuous	32	78.7%	2,972	75	84.0%	2,972
	Linear Probability	Select Binned	280	75.8%	14,726	1,006	78.9%	14,726
	XGBoost	Select Binned	250	80.0%	15,966	979	83.4%	15,966
	XGBoost	Select Continuous	236	81.4%	15,966	955	84.5%	15,966
	XGBoost	All	214	83.6%	15,966	931	87.7%	15,966

Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023.

Notes: Models estimated or trained on 75% of institution-year observations. Predictions and area under the curve (AUC) reported for remaining evaluation observations (25%). Closure is measured both as point-in-time (closed in given year) and in a 3-year window (closed within 3 years of current year). There were 327 actual closures in the 2002-2023 sample and 283 in the 2006-2020 sample.

As shown in **Table 5**, with AUCs approaching or in excess of 80%, most of the models can be considered highly predictive, especially on more well-populated data. But the XGBoost model outperforms the linear probability models consistently on the evaluation dataset (25% of observations). This can be surmised using the combined objectives of predictive accuracy (informed by the AUC) and the ability to consider a fuller set of institutions (informed by the sample size). To illustrate this, it is instructive to follow the progression of predicted closures and AUC across the rows of the upper panel of **Table 5**, which use the full 2002-2023 sample.

Beginning with the linear probability model using continuous controls, the sample size is only 2,624 institution-year observations, which represents only 13% of the available sample, due to the prevalence of the missing data. So although the AUC is a respectable 78.7%, the model predicts only 11 closures because it is unable to generate predictions for the vast majority of institutions. In the next row, we employ the LASSO procedure to restrict the number of covariates to only the most predictive ones, still using continuous controls line in the previous specification. This increases the sample size slightly, improves the AUC to a magnitude comparable to the XGBoost models (79.3%), and increases the number of predicted closures to 32, yet this is still far from the actual number of closed institutions of 327 in the evaluation dataset. Finally, when we use binned controls that include a category for expected missing values for each covariate, we are able to consider most institution-year observations using OLS (15,568, because some observations still get dropped due to unexpected missings), such that the model predicts a more on-target 287 closures. However, the predictive accuracy drops to 75.8%, meaning that the model is able to discriminate less well due to the implicit imputation inherent in using the binning method. In the row that follows, we show that using the XGBoost model on the same binned controls as the OLS significantly improves predictive accuracy to an AUC 79.7% and allows us to consider the full sample of 19,726 institution-year observations in the evaluation data. For that same sample, XGBoost does even better using continuous versions of the binned controls (AUC of 80.9%), and better still using a fullest set of covariates including 4^{th} and 5^{th} lags, county controls, institutional features, and even richer financial metrics (AUC of 82.3%).

In other words, the missing data in our assembled institution-level dataset is costly in terms of predictive power, but the machine learning model can account for the missing data much more effectively than a linear probability model can. Conditional on targeting the same AUC of about 79-80%, there are benefits to using XGBoost compared with binned OLS because researchers can estimate closure probabilities for the full sample of institutions, thereby considering institutions with and without missing data. In other words, machine learning compared with linear probability models can buy researchers either accuracy (higher AUC for same sample relative to linear probability) or reliability when some of the data is missing (same AUC on a larger sample of institutions).

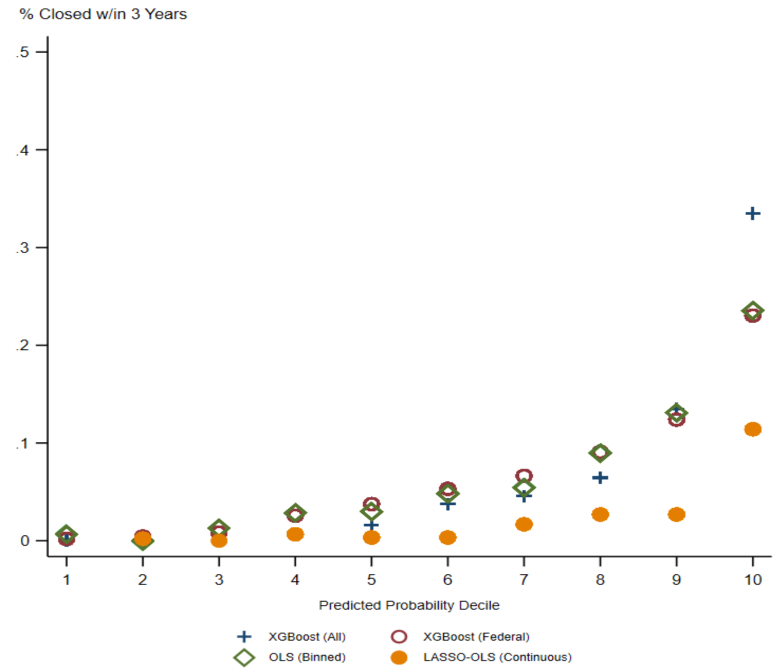
Also in the upper panel of **Table 5**, we provide comparable estimates considering "closed within 3 years" as the closure outcome variable in the last three columns. As before, the relative performance of XGBoost compared with linear probability using the various forms of our covariates is unchanged relative to the point-in-time definition of closure. The peak predictive accuracy we can achieve is considerably better using this definition of "closure," reaching an AUC of 86% in our preferred specification with the richest controls. For simplicity of interpretation, we focus on the predicted probability of closure at a point in time in the sections that follow. That said, we note the promising improvement in predictive performance with the alternative closure metric.

To benchmark our models against existing methods, in the lower panel of **Table 5** we provide estimates of predicted number of closures and AUC for the same models as before, but considering the 2006-2020 period when we have better coverage for the key federal accountability metrics. This allows us to estimate both XGBoost and linear probability models using the two key federal accountability metrics – HCM2 and the FRC score – as key predictors, along with sector and year fixed effects. We can then compare the predictions from these models to predictions from our preferred full models with the richest controls, using the federal metrics models as a useful benchmark for the predictive power of our own models. In the first two rows of the bottom panel of **Table 5**, we show that XGBoost outperforms OLS even on the model with federal metrics, both in terms of AUC and in terms of number of institutions with predictions (and therefore total number of predicted closures). With an AUC of 83.6%, the XGBoost with the richest controls significantly outperforms even the 79.3% AUC of the XGBoost on the federal metrics. That said, we note that the FRC score does have predictive power even controlling for all of the richest financial, student, and staff data. But as a standalone measure, it significantly underperforms the full machine learning model. What is more, the FRC score's usefulness is limited in the broader context of predicting severe financial distress for all institutions since it is only available for private colleges, while our preferred models can be easily estimated for all institutions. Finally, because they are designed as a point-in-time measure, the federal metrics do not benefit from the alternate definition of closure (within 3 years), while the XGBoost model performs even better with the alternate closure definition on the better populated 2006-2020 data than on the 2002-2023 data.

Next, we turn to an analysis of actual and predicted closure probabilities in **Figures 6a-6b**, sorting our predicted values for each model into deciles. We present the share of institutions that actually closed within 3 years by prediction decile in **Figure 6a**. As expected given our relatively high AUCs, the share of institutions that actually closed increases with the predicted probability decile, reaching a high of 34% of institutions closed in the top decile for the XGBoost model with all controls. The XGBoost model with federal metrics and the binned OLS model follow somewhat behind, while the LASSO OLS model performs rather poorly along this dimension. Then in **Figure 6b**, we give a sense of the alignment between predicted and actual closures with the share of institutions that actually closed within 3 years against the share predicted to close in each of our models, for each model's prediction deciles. Once more, XGBoost significantly outperforms the other models. In fact, the model does especially well among the riskiest institutions, showing that some 84% of the 100 institutions with the highest predicted probability of closure actually closed within 3 years, compared with 47% for the federal metrics model and 61% for OLS with binned controls.

Figure 6a – Relationship between Predicted and Actual Closures,

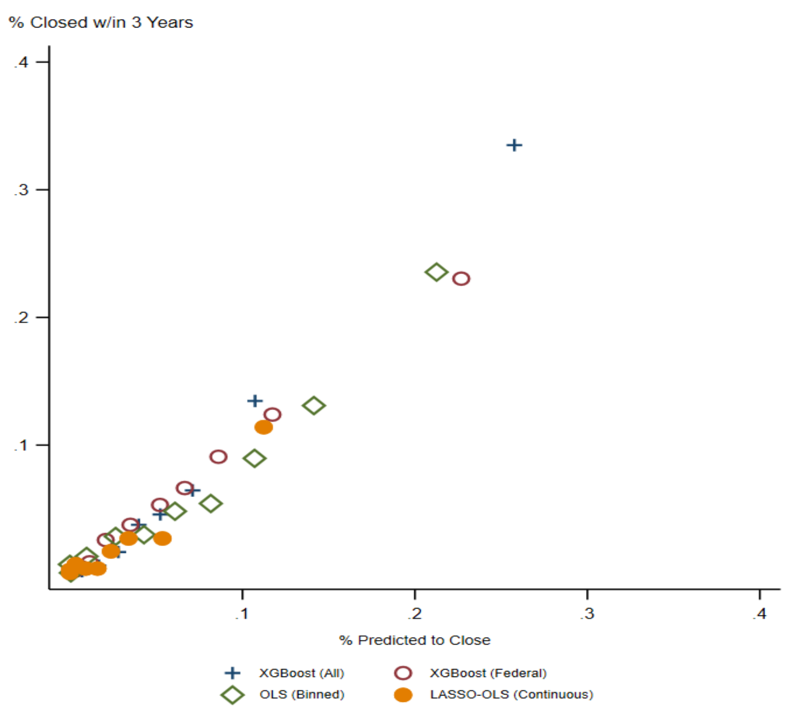
Share Institutions Closed by Prediction Decile, 2006-2020



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

Figure 6b – Relationship between Predicted and Actual Closures,

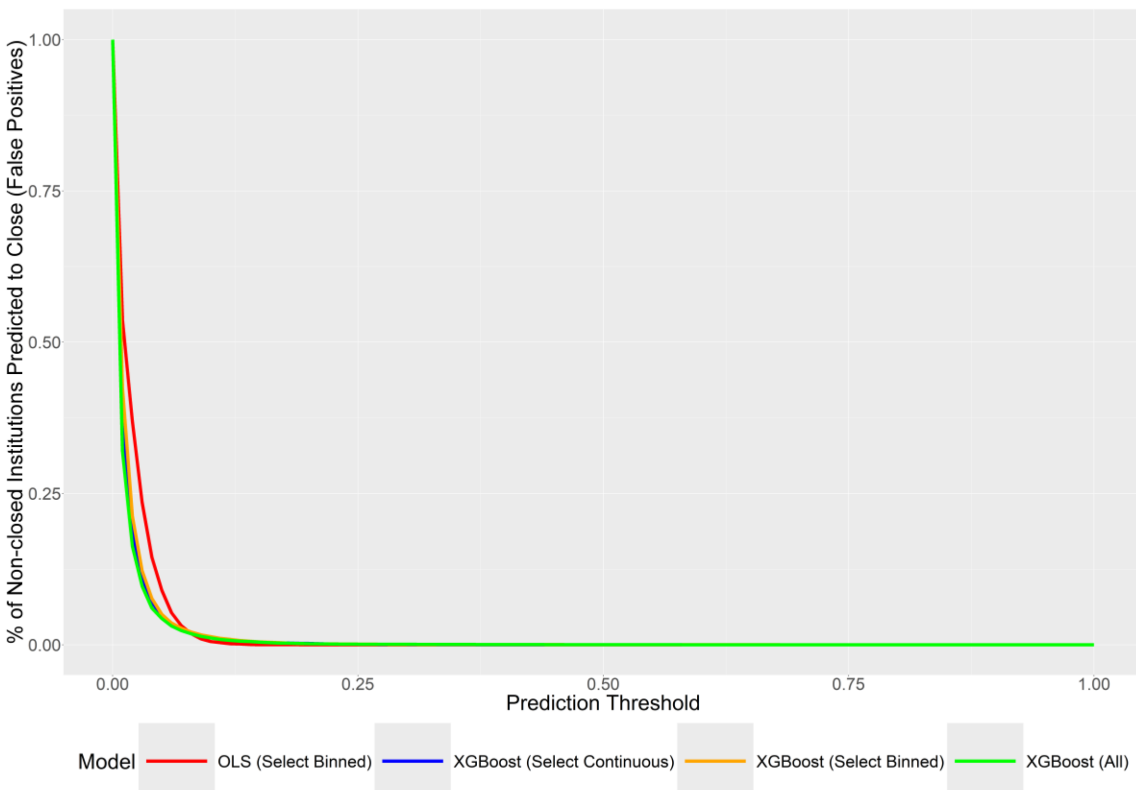
Actual v. Predicted Closures for Each Prediction Decile, 2006-2020



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

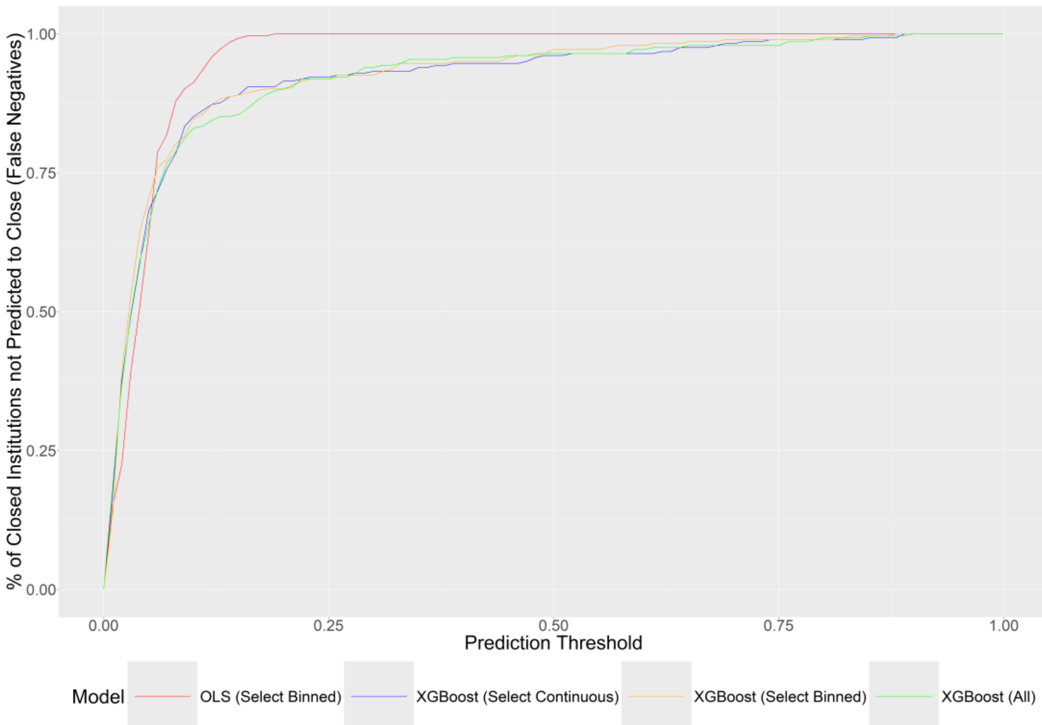
Next, we consider the performance of our models under simple binary sorting mechanisms, displaying the implied false positive/negative rates conditional on a chosen threshold of "predicted closure." In other words, we show the false positive/negative rates based on the threshold at which an institution would be predicted to close for each of the models in **Figures 7a-7b**, below. All models have relatively low false positive rates, even at low thresholds, though the XGBoost false positive rates are a little lower (**Figure 7a**). Yet **Figure 7b** shows that false negative rates conversely are quite high even at low thresholds. This is because the distributions of predicted probabilities are skewed strongly to the left, as shown in **Figure 8**. This is to be expected given that closure is a rather rare event.

Figure 7a – False Positive Rates for Closure Predictions, by Model, 2002-2023



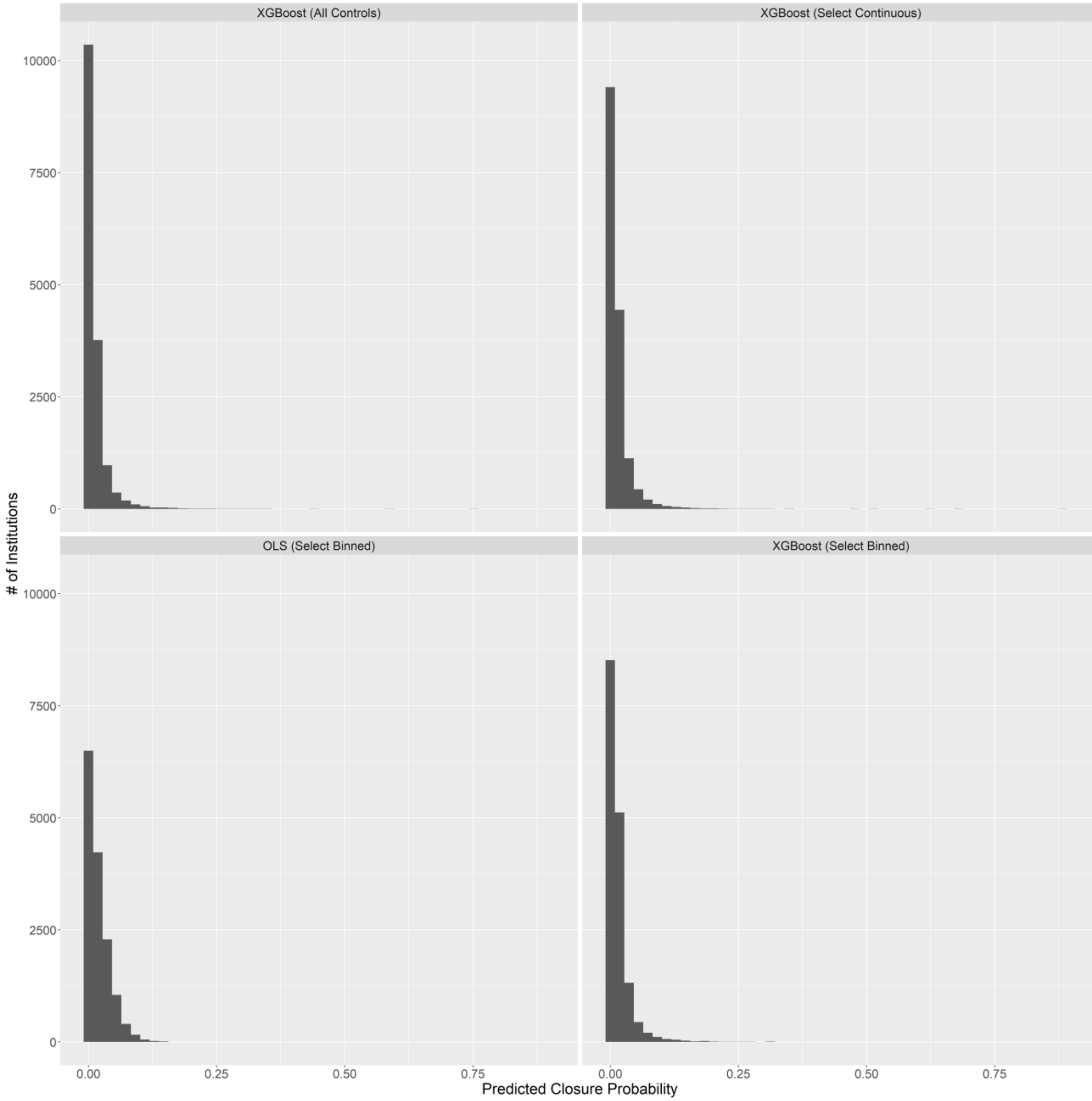
Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

Figure 7b – False Negative Rates for Closure Predictions, by Model, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

Figure 8 – Distribution of Predicted Closure Probabilities by Model, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

Consistent with our AUC measures, the machine learning model has lower false negative rates at moderate thresholds, as shown **Figure 7b**. This is because the right tail of the distribution of predicted closure probabilities is thicker and longer for this model relative to any of the three linear probability models. The sector-specific predicted closure probability distributions, included in **Appendix Figures A1a-A1d**, show that the improvement in accuracy in the right tail for the machine learning model comes predominantly from more accurately predicting closures of for-profit institutions. This is partially an artifact of the larger share of true positives that come from this segment, yet might be an appealing feature for regulatory or accrediting agencies.

Overall, the XGBoost algorithm performs considerably better in predicting institutions with very high probabilities of closure. To provide further insights regarding the accuracy of the models, we compare the ability of multiple models to correctly predict closures in the cases that were viewed as having the highest likelihood of closure within three years. Restricting our attention to the subset of the evaluation datasets for which there are complete data (15,966 institution-year observations), 83 of the 100 observations with the highest predicted closure probabilities and 278 of the 500 observations with the highest predicted closure probabilities from the XGBoost model with all available controls closed within three years. Meanwhile, our OLS models with binned controls had insufficient data to estimate data on 1,240 observations (including 79 closures) and only saw 46 of the 100 highest predictions and 177 of the 500 highest predictions closed within three years.

B. Feature Importance Across Models

As noted above, the majority of our analysis focuses on predictive power and accuracy of the overall models. This is done for two related reasons. First, without a causal research design, the interpretation of individual coefficients is correlational, at best. Second, the fact that many variables are highly correlated with one another, and in many cases functions of one another, makes any interpretation of magnitude very difficult. For instance, the Financial Responsibility Composite Score is a function of a number of different financial metrics. These metrics are either directly or indirectly in our models (or at least at risk of being selected by the LASSO procedure). These metrics themselves are then functions of other key variables such as enrollment and the recent change in enrollment. In other words, it is difficult to interpret even the magnitude of any given coefficient because it is non-sensical to discuss the partial effect (e.g., holding all other variables constant) when that cannot conceivably happen in most cases. Having these various classes of variables in the model is still very important for predictive reasons, particularly because non-linearity is of outsized importance for predicting rare and extreme events such as the closure of an institution.

However, while the magnitude of coefficients is difficult (in the case of OLS) or impossible (in the case of some machine learning models) to quantify, this does not mean that we cannot provide evidence on the relative importance of different covariates. **Table 6** presents measures of relative importance for variables in five of the predictive models on which we focused. For each of the three

XGBoost models, relative importance is measured by the gain in predictive power from models that include the variable compared with models that do not include it, averaged over every version of each model estimated. For the two OLS models presented in **Table 6**, variables are ranked based on their p-values, and standardized coefficients are included.[5]

While we don't want to focus on any given variable for the reasons discussed above, there are still some broad takeaway messages from **Table 6** that may be useful for researchers and policymakers. First, reassuringly, the variables that should have a strong theoretical impact on the likelihood of closure (e.g., measures of financial distress) are well-represented across all models. Second, particularly for the XGBoost models, variables measuring ratios of financial metrics and those measuring changes in covariates are generally more important than those measuring the level of those covariates. This is an intuitive finding, and argues for the inclusion of recent trajectory as an important metric that should be considered by monitoring agencies in addition to absolute levels, but is not currently part of federal accountability policy.

Comparing the classes of variables that are identified as influential in the XGBoost compared with OLS models, we can again find support for the utility of machine learning methodology in predicting closures. Firstly, year and sector fixed effects are much more important predictors in the OLS models. But in the XGBoost models, which allow for more complex interactions and non-linear relationships, it is the underlying metrics (e.g., financial conditions) which are of greater relative importance. In OLS models, it is thus more common for the model to imply "there is something about this year or sector which is important, but we don't know what it is," while machine learning models can better identify which underlying metrics are actually important. This is especially relevant from the perspective of monitoring, as a year fixed-effect (e.g., the knowledge of whether a given year had many or few aggregate closures) is not available until after a closure takes place. To put it differently, year effects may be useful in predicting past closures, but not future ones.

Finally, we note that all models indicate that a portion of closure propensity for private non-profit 4-year institutions cannot be captured very well by the observables. This speaks to idiosyncratic, unobservable factors like governance likely affecting closure. That said, the machine learning models – especially those with the richest covariates – generally perform quite well in explaining financial distress among for-profit institutions using available historical data.

[5] For the most part, the variables with the strongest p-values also happen to be those with the highest standardized coefficients in the OLS models.

Table 6 – Key Predictors of Closures and Contribution to Prediction, Select Models, 2002-2023

XGBoost Models

XGBoost (All Controls)		XGBoost (Continuous)		XGBoost (Binned)	
Covariate	**Gain**	**Covariate**	**Gain**	**Covariate**	**Gain**
L2 FRC score	3.9%	L2 Instructional % staff	3.7%	PNFP 4-year	4.5%
PNFP 4-year	2.3%	L2 Revenue % change	3.3%	L2 Enrollment % change 1stQ	2.6%
L2 Revenue % change	2.0%	L3 Enrollment % change	3.1%	L3 Enrollment % change 1stQ	2.6%
L2 Instructional % staff	2.0%	L2 Staff % change	3.0%	PFP 2-year	2.1%
L2 Staff % change	1.8%	L2 Enrollment % change	3.0%	L2 Salaries % expenses 1stQ	2.1%
L2 Operating margin	1.8%	L3 Revenue % change	2.9%	L2 Staff % change 1stQ	2.1%
L2 Enrollment % change	1.6%	PNFP 4-year	2.9%	L3 Gifts % revenue 1stQ	2.0%
L2 Salaries % expenses	1.5%	L2 Operating margin	2.8%	L2 Log unrestricted assets 4thQ	1.7%
L2 Log unrestricted assets	1.5%	L2 Log unrestricted assets	2.6%	L2 Revenue % change 1stQ	1.7%
L3 Revenue % change	1.5%	L3 Tuition % revenue	2.4%	L3 Revenue % change 1stQ	1.5%
L3 Enrollment % change	1.4%	L2 Tuition % revenue	2.3%	L2 Investment % revenue 1stQ	1.4%
L2 10% enrollment drop 5 years	1.3%	L2 Instructional % expenses	2.2%	L3 Staff % change 1stQ	1.3%
L2 Tuition % revenue	1.2%	L3 Staff % change	2.0%	L2Gifts % revenue 1stQ	1.3%
L4 Revenue % change	1.2%	L2 Log revenue	2.0%	L2 Interest % expenses 1stQ	1.1%
L2 Log revenue	1.1%	L3 Instruction % expenses	1.9%	L2 DCOH 3rdQ	1.1%
L4 Enrollment % change	1.1%	L2 Log staff	1.9%	L2 HCM2	1.1%
L2 Log staff	1.1%	L2 Fulltime % staff	1.9%	L2 Instruction % expenses 1stQ	1.0%
L4 FRC Score	1.1%	L3 Operating Margin	1.8%	L2 Tuition % revenue 4thQ	0.9%
L2 Log enrollment	1.1%	L2 Log expenses	1.7%	Year = 2018	0.9%

Linear Probability Models

OLS (Binned)			OLS - Lasso (Continuous)		
Variable	Standardized Coeff	P-Value	Variable	Standardized Coeff	P-Value
L2 HCM2	0.8%	0.00	L3 DCOH	5.7%	0.00
L2 Instruction % staff 4thQ	-1.1%	0.00	L2 DCOH	-5.7%	0.00
L2 staff % change 1stQ	0.5%	0.00	L2 Instruction % expenses	-1.6%	0.00
L2 Instruction % staff 1stQ	-1.1%	0.00	L3 Log expenses	13.3%	0.00
L2 Instruction % staff 2ndQ	-1.1%	0.00	L2 Log expenses	-13.0%	0.00
L2 Instruction % staff 3rdQ	-1.0%	0.00	L3 Instruction % expenses	1.5%	0.00
Year = 2018	0.4%	0.00	Year = 2018	0.6%	0.00
L2 Log EBIDA 2ndQ	-0.9%	0.00	L3 HCM2	0.6%	0.00
L2 Depreciation % expenses 1stQ	-0.6%	0.00	L2 Staff % change	0.5%	0.00
L3 HCM2	-0.5%	0.00	L3 Enrollment 5% drops for 3 yrs	0.4%	0.00
L2 Log EBIDA 3rdQ	-0.9%	0.00	L3 Enrollment % change	-0.4%	0.00
PFP 2-year	6.1%	0.00	L3 DCOH % change	0.4%	0.00
L2 Log EBIDA 1stQ	-0.7%	0.00	Year = 2014	0.3%	0.00
PFP 4-year	2.8%	0.00	L2 DCOH % change	0.4%	0.00
PNFP 2-year	2.5%	0.00	Year = 2016	0.3%	0.01
PNFP 4-year	5.1%	0.00	L3 Fulltime % staff	-0.7%	0.02
L2 DCOH 1stQ	0.7%	0.00	L2 Enrollment 5% drops for 2 yrs	0.2%	0.02
Year = 2015	0.3%	0.00	Year = 2013	0.3%	0.02
L2 Unrestricted assets 2ndQ	-0.6%	0.00	L2 Instruction % expenses	-0.5%	0.02

Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

C. Closure Predictions – Targeting Annual Closures

Next, we consider the potential performance of a screening mechanism targeting the predicted number of closures (i.e., the sum of predicted closure probabilities) comparable in magnitude to the actual number of closures. In other words, with the predicted probabilities in hand, what would happen if we selected the "optimal" screening method for detecting institutions likely to close by selecting the optimal prediction threshold such that we predict approximately the correct number of closures in our evaluation dataset (again, the 25% of data withheld from the training models)? Since closure is such a low probability event, setting the target threshold low enough to only predict the relatively few closures that actually occur implies rates of false positives and true negatives that leave much to be desired. Of the 327 actual closures in the 2002-2023 evaluation dataset, the XGBoost model predicts very few institutions accurately, and the binned linear probability model even fewer; the remaining institutions flagged as "likely to close" based on the implied threshold are all false positives.

Because of the missing data, the linear probability model with binned covariates detects only 29 closed institutions, or less than 10% of the total closures in the evaluation dataset. The false positive rate appears relatively low only because the models are unable to provide any prediction for the vast majority of institutions, including the vast majority of institutions that closed. This exercise illustrates a key feature of prediction models on low-probability outcomes: they are not terribly good at *simultaneously* predicting the correct number of closures and predicting the timing of those few closures very accurately.

D. Closures Predictions – Targeting True Positive Rates

To illustrate the predictive capabilities of the models, we use each of them in a simple screening methodology based on a target true positive rate. We consider: what would be the true/false positive/negative rates if, for each model, we selected the threshold such that we detect *at least* 50%, 60%, 70%, or 80% of true positives?[6] In other words, how many institutions would a regulatory or accrediting agency have to monitor in order to "catch" most of the real closures? As we discussed previously, the predicted closure probabilities our models output can be used in a variety of ways, including many more complex than what we consider here. For example, an economical auditor will know to rank order institutions and then select the share to audit in a stratified manner, sampling a

[6] In our application, targeting a true positive rate of 90% would cause the optimal threshold to be close to 0, such that nearly 100% of institutions that did not close to be predicted to close, so we omit the results for brevity.

higher share of institutions with higher predicted closure probabilities. We are not suggesting that the exercise we conduct here is in any way prescriptive as to the optimal screening technology, but rather illustrative of the tradeoffs between the models and the clear improvement in performance of the XGBoost model with all controls.

The results of this illustrative example are presented in **Table 7**. The clear tradeoff between the target true positive rate and the false positive rate with a prediction algorithm that has any power to discriminate, as ours do, is evident here. The false positive rate (% of total institutions that did not close but were predicted to close) for the best-performing model, XGBoost, ranges from 11% in the full sample with a true positive rate of 51% to 49% when the true positive rate is 92%. In other words, a regulator would have to screen only a tenth of institutions in order to detect half of true closures, but a full half of institutions in order to detect 92% of true closures – even for institutions with (some) missing data. Screening about a third of institutions (false positive rate of 36%) with XGBoost would detect over 80% of true closures (true positive rate of 82%), and so forth.

While the binned OLS model appears to have generally similar false positive rates to XGBoost, this is the case only because it is unable to produce any prediction at all for 18% of institutions due to unexpected missing values. And XGBoost with the full set of controls consistently outperforms the model with federal metrics, especially at higher target thresholds for true positives. For example, if a regulator wanted to detect 90% or more closures, the model with all controls could would have a false positive rate of 49%, and the federal metrics model 54%. Finally, using the LASSO OLS produces clearly inferior results in this exercise. Because the model cannot provide a prediction of any kind for the 93% of observations with at least one missing covariate, the calculated false positive rates out of the full sample are misleadingly low. In fact, the upper bound on a true positive rate is 7%, even if screening all the 2,950 institutions in the relevant sample.

To summarize, **Table 7** suggests that lower false positive rates (in other words, fewer institutions requiring screening for a given true positive rate) using the target threshold method are associated with a) the full sample compared with non-missing sample, and c) the XGBoost algorithm compared with the linear probability models, and c) the full available metrics compared with the federal metrics.

Table 7 – Predictive Power Based on Target True Positive Rate, by Model, 2002-2023

Sample	Model	Controls	Closures		Non-Closures		Target % of True Positives In Sample	Implied Threshold	True Positives			False Negatives			False Positives			Closures w/ No Prediction	
			In Sample	Total	In Sample	Total			#	% in Sample	% of Total	#	% in Sample	% of Total	#	% in Sample	% of Total	#	% of Total
2006-2020	XGBoost	Federal Metrics	283	283	15,683	15,683	50%	0.029	158	56%	56%	125	44%	44%	2,391	15%	15%	0	0%
2002-2023	OLS	Select Binned	269	327	15,299	19,435	50%	0.037	135	50%	41%	134	50%	41%	2,424	16%	12%	58	18%
2002-2023	XGBoost	Select Continuous	327	327	19,435	19,435	50%	0.025	166	51%	51%	161	49%	49%	2,300	12%	12%	0	0%
2002-2023	XGBoost	All	327	327	19,435	19,435	50%	0.024	167	51%	51%	160	49%	49%	2,062	11%	11%	0	0%
2002-2023	OLS LASSO	Select Continuous	23	327	2,950	19,435	50%	0.057	12	52%	4%	11	48%	3%	98	3%	1%	304	93%
2006-2020	XGBoost	Federal Metrics	283	283	15,683	15,683	60%	0.025	170	60%	60%	113	40%	40%	2,904	19%	19%	0	0%
2002-2023	OLS	Select Binned	269	327	15,299	19,435	60%	0.029	167	62%	51%	102	38%	31%	3,604	24%	19%	58	18%
2002-2023	XGBoost	Select Continuous	327	327	19,435	19,435	60%	0.017	210	64%	64%	117	36%	36%	4,191	22%	22%	0	0%
2002-2023	XGBoost	All	327	327	19,435	19,435	60%	0.016	217	66%	66%	110	34%	34%	3,794	20%	20%	0	0%
2002-2023	OLS LASSO	Select Continuous	23	327	2,950	19,435	60%	0.023	14	61%	4%	9	39%	3%	387	13%	2%	304	93%
2006-2020	XGBoost	Federal Metrics	283	283	15,683	15,683	70%	0.02	202	71%	71%	81	29%	29%	4,326	28%	28%	0	0%
2002-2023	OLS	Select Binned	269	327	15,299	19,435	70%	0.024	189	70%	58%	80	30%	24%	4,574	30%	24%	58	18%
2002-2023	XGBoost	Select Continuous	327	327	19,435	19,435	70%	0.014	235	72%	72%	92	28%	28%	5,080	26%	26%	0	0%
2002-2023	XGBoost	All	327	327	19,435	19,435	70%	0.014	230	70%	70%	97	30%	30%	4,372	22%	22%	0	0%
2002-2023	OLS LASSO	Select Continuous	23	327	2,950	19,435	70%	0.009	17	74%	5%	6	26%	2%	919	31%	5%	304	93%
2006-2020	XGBoost	Federal Metrics	283	283	15,683	15,683	80%	0.014	233	82%	82%	50	18%	18%	6,285	40%	40%	0	0%
2002-2023	OLS	Select Binned	269	327	15,299	19,435	80%	0.015	217	81%	66%	52	19%	16%	6,740	44%	35%	58	18%
2002-2023	XGBoost	Select Continuous	327	327	19,435	19,435	80%	0.011	266	81%	81%	61	19%	19%	7,300	38%	38%	0	0%
2002-2023	XGBoost	All	327	327	19,435	19,435	80%	0.01	268	82%	82%	59	18%	18%	6,990	36%	36%	0	0%
2002-2023	OLS LASSO	Select Continuous	23	327	2,950	19,435	80%	0.004	19	83%	6%	4	17%	1%	1,322	45%	7%	304	93%
2006-2020	XGBoost	Federal Metrics	283	283	15,683	15,683	90%	0.008	257	91%	91%	26	9%	9%	8,448	54%	54%	0	0%
2002-2023	OLS	Select Binned	269	327	15,299	19,435	90%	0.004	244	91%	75%	25	9%	8%	9,971	65%	51%	58	18%
2002-2023	XGBoost	Select Continuous	327	327	19,435	19,435	90%	0.007	297	91%	91%	30	9%	9%	9,855	51%	51%	0	0%
2002-2023	XGBoost	All	327	327	19,435	19,435	90%	0.006	300	92%	92%	27	8%	8%	9,614	49%	49%	0	0%
2002-2023	OLS LASSO	Select Continuous	23	327	2,950	19,435	90%	0	23	100%	7%	0	0%	0%	2,950	100%	15%	304	93%

Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023
Notes: Models estimated or trained on 75% of institution-year observations; predictions reported for remaining 25% of observations. Closure is measured as point-in-time (closed in the evaluation year).

E. Case Studies of College Closures

To provide some context for our predictions, we examined a few case studies using the results from our models predicting closure within the next three years. The XGBoost models predicted an average likelihood of closure of about .058, while the linear regression models predicted an average likelihood of about .068.

Our first case study is Birmingham-Southern College, which closed after the spring 2024 semester following years of very public financial stress and a failed effort to get a bond from the state of Alabama (Korn, 2024). None of the models accurately reflected the risk that the college faced, with the closure probability being at the median of private nonprofit colleges. This could be because it did not have concerns with federal accountability metrics and had a relatively strong balance sheet due to its historic endowment even as net operating losses were common. This reinforces the limitation of the models in accurately predicting idiosyncratic closures of private non-profit 4-year institutions, where unobservable (to the researcher) governance and specialized reasons leading to closure are concealed by financial performance that does not necessarily give rise to concerns.

On the other hand, the models strongly predicted the closure of Judson College in Alabama in 2021. Our XGBoost models had predicted probabilities of as high as 0.25 in 2019 and 0.29 in 2020, including being rated as the seventh most likely private nonprofit college to close in 2020. Meanwhile, closure probabilities in the XGBoost models using federal data only remained below average. Closure risks in the OLS models also remained near or below the sample average for Judson, although some years were not calculable due to missing data (highlighting the value of XGBoost models). Overall, 52 of the 100 riskiest private nonprofit observations and 120 of the 500 predicted as most likely to close in the XGBoost models closed within three years. Only 70 of the other 7,034 observations closed, suggesting that focusing on the riskiest cases would capture most closures even if some recent closures such as Birmingham-Southern, Iowa Wesleyan, and the University of the Arts would be missed.

The models generally had stronger predictive power in the for-profit sector. An example is the Marinello School of Beauty chain, which closed in 2016. Between 2011 and 2016, the predicted probability of closure rose from nearly the sample mean to over 0.50, while there was generally too much missing data to generate a closure prediction using OLS models. Similar successful flagging of closures using XGBoost models while frequently having insufficient data for OLS predictions occurred at Everest Colleges (closed in 2017) and the Art Institutes (closed in 2018). Overall, the XGBoost models correctly identified 84 of the riskiest 100 observations and 266 of the riskiest 500 observations as closing within three years, while the closure rate among observations outside of the top 500 was about seven percent.

VI. Simulated Increases in Closures due to Potential Enrollment Changes

In addition to using model output to identify institutions at risk of closure, we can also simulate the impact of recent and projected future enrollment declines. For simplicity and interpretability, we do so using the continuous covariates OLS model using LASSO-determined optimal controls (including enrollment). The parameters from this model are scaled up to the most recent population of all private non-profit and for-profit colleges. In other words, we are making the assumption that no public institutions will (be allowed to) close.

Using 2019 as a baseline (to avoid contamination by COVID-19 induced disruptions), if the enrollment declines that colleges have experienced since then persisted into the future (no recovery or further decline), we can expect to see an additional 1.1 closures per year (an increase of 2% over the average annual closures). Assuming the worst-case scenario predictions come to pass from the upcoming demographic cliff (or a 15% decline in enrollment), there could be as many as 71 (126% of the average annual closures) immediate closures, and an annual increase in the rate of closures of 4.8 (an increase of 8.5% over the average annual closures). Looking instead at a measure of severe financial distress, such as a persistently negative operating margin, the analogous numbers would be an addition 21 institutions annually if current trends persist, and an additional 99 under the worst case predictions following the demographic cliff.

Table 8 presents the predicted number of students, faculty, staff, and expenses which would be predicted to be affected by the continuous LASSO model, should these additional closures occur. These simulations point to the precarious potential situation facing postsecondary education in the coming years, especially if the demographic cliff materializes in a moderate to severe fashion. While some of these estimated increases might seem small at a national level, they would be significant for the handful of localities predicted to experience college closures in a given year. It is important to reiterate that most institutions that close are somewhat smaller than average, with the median closed school enrolling a student body of about 1,389 full-time equivalent students several years prior to closure, though the distribution is skewed. This means that, even if our projections are accurate, many (if not all) of these additional predicted closures are unlikely to be institutions known outside of their local communities or states, yet their closures could be quite disruptive to those communities. Some institutions can be considered significant employers even in small/modest size communities.

Table 8: Predicted Additional Annual Closures under Selected Scenarios, 2019

	(1) 2019 Enrollment Patterns Continue	(2) Demographic Cliff (annual, worst-case)	(3) Demographic Cliff (one-time, worst-case)
Institutions	1.1	4.8	71
Students	1,389	7,656	89,673
Staff	287	1,252	18,531
Expenses	\$16.9m	\$73.9m	\$1,093m

Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 2002-2023

Notes: Predictions are based on the outlined scenarios and predictions from the continuous OLS model with LASSO-selected covariates, scaled up to the full sample of private institutions in the IPEDS data.

Even ignoring the potential negative effects due to reduced training capacity in a county which loses a college, the immediate employment effects as a share of the labor force might be large. This includes not only the loss in employment coming directly from the college, but also the immediate spillovers from establishments that provide goods/services to schools (most notably, retail, healthcare, and food serviced). Moreover, most students work while attending college, so any working students who are either attracted to/kept from leaving the community due to the presence of the institution will also contribute to local economic effects.

VII. Discussion

Colleges and universities are facing unprecedented fiscal challenges in today's economic climate. The cost of education is rising, while many colleges have faced enrollment challenges over the last decade. The COVID-19 pandemic did not directly result in the anticipated increase in college closures due to a timely and substantial influx of federal funds. However, the resulting enrollment decline and period of relatively high inflation has exacerbated many institutions' liquidity, and even solvency, concerns. Moreover, many funding streams – exemplified, perhaps, by federal financial aid – are active areas of public policy and administration. Yet both the precursors to colleges' fiscal challenges are an understudied area in higher education finance, even as the economic importance of institutions of higher education has grown significantly over the past century as college attendance rates have steadily climbed.

Our study contributes to this literature by examining the extent to which college financial distress – exemplified, in its most severe form, by full institution closures – can be predicted in advance based on publicly available data. We assemble the most comprehensive dataset to date on the characteristics of colleges and universities, including dates of operation, institutional setting, student body, staff, and finance data from 2002-2023. We provide an extensive description of what is known and unknown about closed colleges compared with institutions that did not close. Then we develop a series of predictive model of severe financial distress for colleges and universities, incorporating a range of predictors, from operational revenue and expense patterns, to sources of revenue, to metrics of liquidity and leverage, to declining enrollment patterns, and prior signs of significant financial strain. Our preferred model using modern tools of machine learning significantly outperforms models based on existing federal accountability metrics, as well as linear probability models with richer covariates. We highlight the significant concern of missing data that can render more traditional estimation methods less effective than machine learning algorithms.

We then use our predictions to document our estimated increase in the likelihood of future closures due to commonly predicted scenarios. In particular, we focus on enrollment declines – both temporary, such as those that arose during the COVID-19 pandemic, and systemic, like those resulting from predicted future demographic changes – which are often accompanied by fiscal challenges and represent one of the strongest explanatory variables in our predictive models. We conclude that the demographic cliff is predicted to significantly increase the number of institutions at risk of severe financial distress, including closure.

As future research, it would be valuable to estimate the impact of college closures and severe financial stress on county-level measures of employment and wages, and population. This would be an important addition to the literature because of the role that higher education institutions, particularly in the nonprofit sector, play as anchor institutions in the local community. We are particularly interested in the effect of these college-induced disruptions on temporary or permanent reallocations of human capital and employment within and across local and regional economic areas.

We caution that our earlier emphasis of negative effects of college financial distress and closures should not be taken to suggest that regulators or localities should seek to prevent college closures. A comprehensive welfare analysis is likely to show that institutions of higher education (and particularly those in the for-profit sector) do not close randomly or without cause. If these institutions are unable to produce outcomes that students, employers, or society at large find valuable, then they should not be artificially sustained by governments absent significant evidence of positive externalities. Indeed, extending the existence of an educational institution destined for failure may actually compound the locality's fiscal problems if the college is never able to survive on its own.

While our predictive models of college financial distress and closure may not be able to accurately predict the eventual failure of each individual institution, they are certainly effective at capturing the riskiest institutions. For example, of the 100 institutions with the highest predicted probability of closure for our preferred model, 84% of colleges actually closed within 3 years. The methods we outline may also be useful to various levels of government preparing for sector-level disruptions and their subsequent economic fallout. Indeed, our results suggest that local communities may be able to anticipate and prepare for labor market and infrastructure disruptions if a college closing appears imminent and be prepared to use whatever levers available to support affected community members and businesses during the transition.

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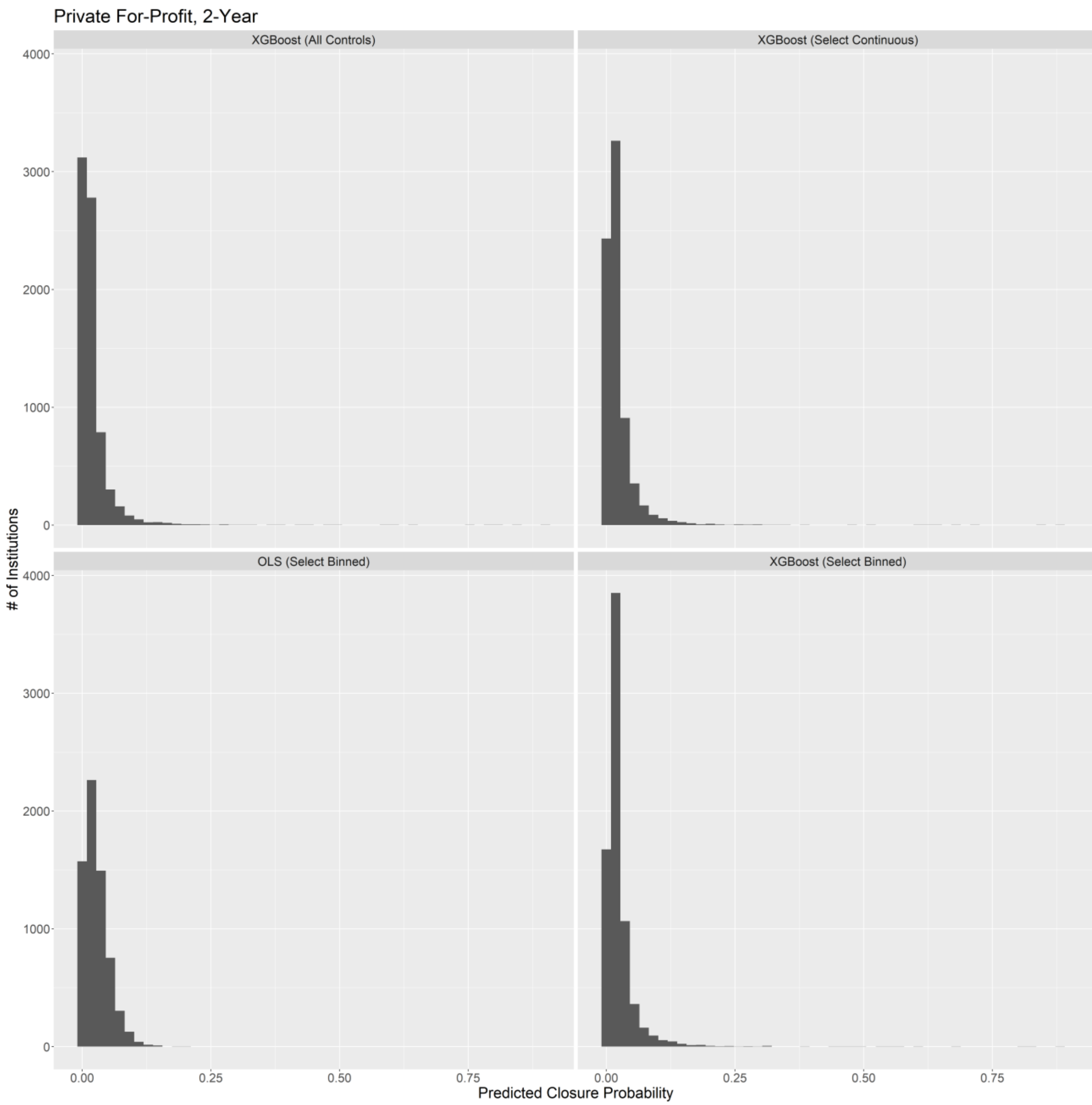
Appendix A

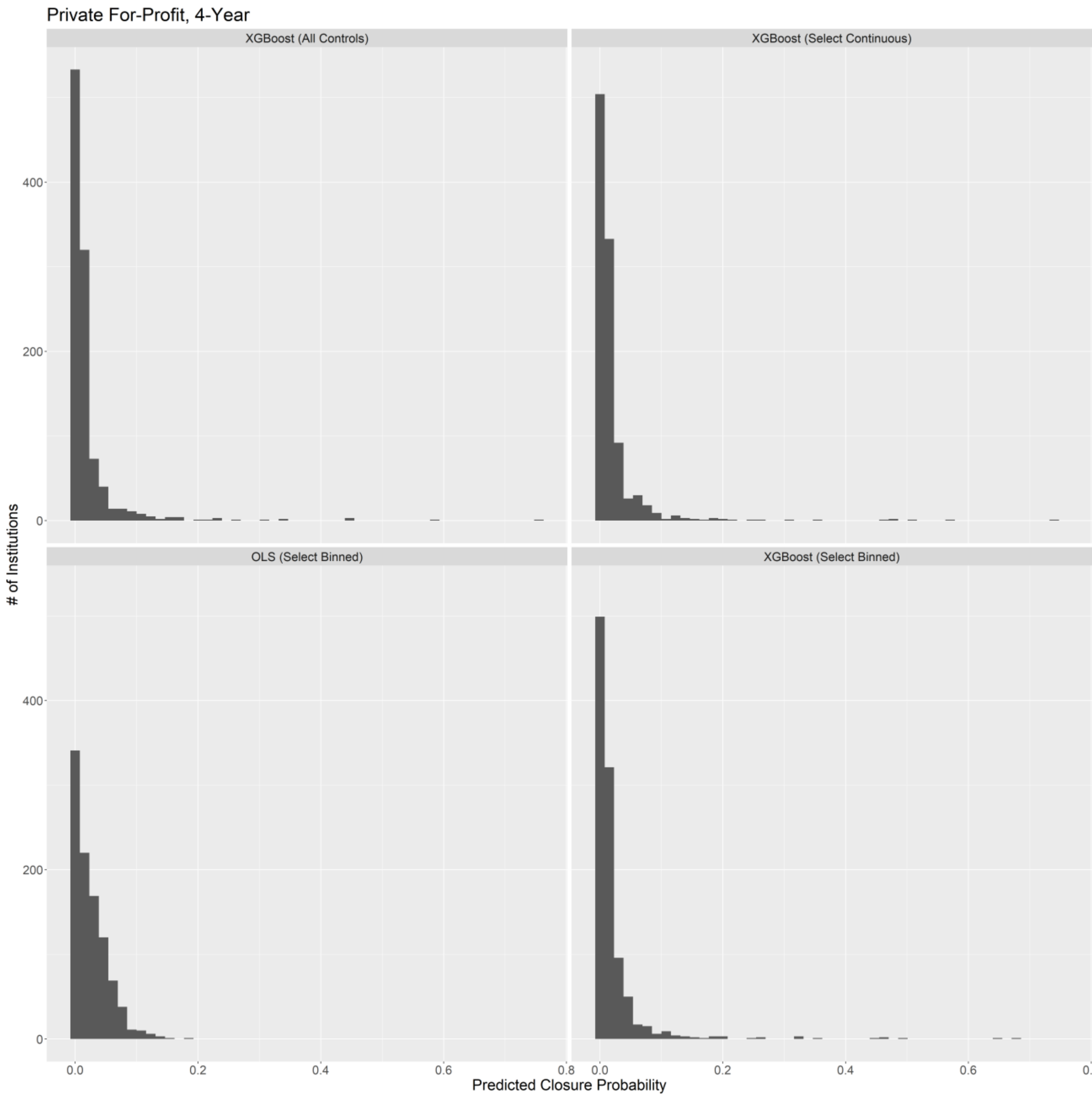
Figure A1a - Distributions of Closure Predictions by Model, Private For-Profit 2-Year, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 1996-2023

Notes: Notes: Models estimated or trained on 75% of institution-year observations; distribution of predicted values reported for remaining evaluation observations (25%).

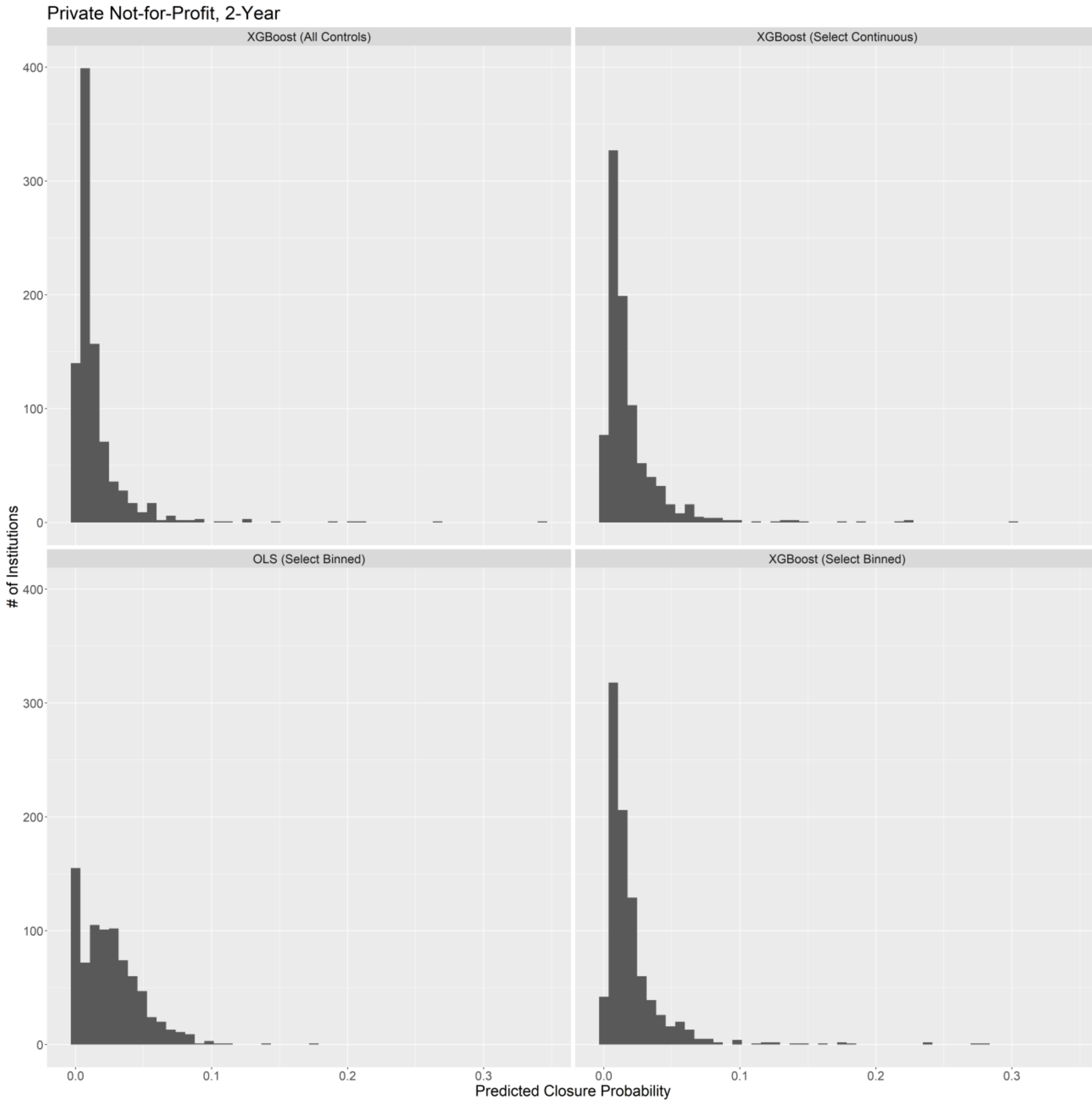
Figure A1b - Distributions of Closure Predictions by Model, Private For-Profit 4-Year, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 1996-2023

Notes: Notes: Models estimated or trained on 75% of institution-year observations; distribution of predicted values reported for remaining evaluation observations (25%).

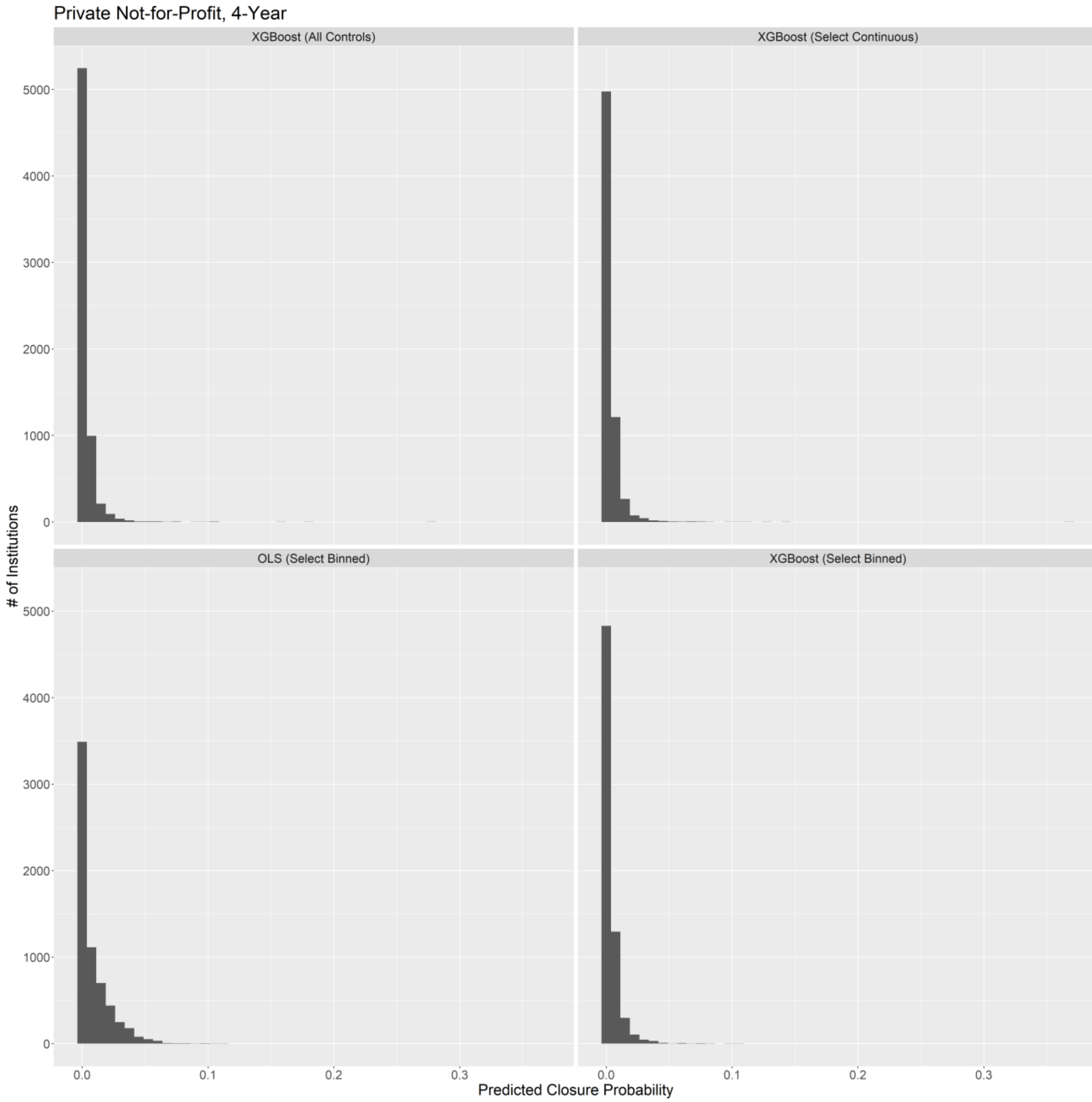
Figure A1c - Distributions of Closure Predictions by Model, Private Non-Profit 2-Year, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 1996-2023

Notes: Notes: Models estimated or trained on 75% of institution-year observations; distribution of predicted values reported for remaining evaluation observations (25%).

Figure A1d - Distributions of Closure Predictions by Model, Private Non-Profit 4-Year, 2002-2023



Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 1996-2023

Notes: Notes: Models estimated or trained on 75% of institution-year observations; distribution of predicted values reported for remaining evaluation observations (25%).

Table A1 – Descriptive Statistics, 2002-2023

		Never-Closed Institutions			Closed Institutions (2 yrs Earlier)		
Covariate Type	**Covariate**	**Mean**	**Median**	**% w/ Data**	**Mean**	**Median**	**% w/ Data**
Accountability Metrics	Heightened Cash Monitoring (Level 2)	1%	No	100%	1%	No	100%
	Financial responsibility composite score	2.3	2.5	37%	1.8	2.0	5%
Financial Performance	Operating margin	4.1%	9.2%	79%	-44.8%	3.0%	10%
	Persistently negative operating margin	15.7%	No	69%	35.5%	No	28%
	YOY change, operating margin	0%	0%	77%	-2%	0%	10%
	Days cash on hand (DCOH)	170.3	11.4	100%	10.1	0.0	100%
	YOY change, DCOH	-339%	0%	99%	-2158%	0%	100%
	Debt ($mil)	94.9	5.4	59%	2.3	0.0	4%
	EBIDA ($mil)	19.0	1.7	79%	0.2	0.0	10%
	Debt to EBIDA	-123.2	0.9	54%	-4.6	0.0	4%
	Debt to assets	2399.7	0.0	75%	0.0	0.0	12%
	YOY change, debt to assets	-1%	0%	74%	-2%	0%	12%
	Unrestricted net assets ($mil)	72.2	2.1	93%	2.7	0.0	16%
Revenue	Total revenue ($mil)	138.8	23.3	93%	6.1	1.5	16%
	YOY change, total revenue	5%	2%	92%	-13%	-2%	16%
	Revenue 10% lower than 5-year high	40%	No	92%	86%	Yes	16%
	Tuition/total revenue	48%	45%	93%	77%	86%	16%
	Auxiliary/total revenue	7%	4%	75%	3%	0%	8%
	Investment revenue/total revenue	3%	0%	93%	1%	0%	16%
	Gifts, grants, contracts/total revenue	4%	0%	82%	1%	0%	16%
Expenses	Total expenses ($mil)	130.5	22.6	93%	6.5	1.5	16%
	Instructional/total expenses	40%	37%	93%	45%	38%	16%
	Scholarships/total expenses	16%	13%	93%	6%	0%	16%
	Interest/total expenses	1%	1%	79%	1%	0%	10%
	Depreciation/total expenses	5%	5%	79%	3%	2%	10%
Staff	Total staff	689.0	195.0	94%	33.7	11.0	18%
	YOY change, total staff	3%	1%	91%	-8%	0%	18%
	Instructional/total staff	50%	50%	89%	52%	50%	13%
	Full-time/total staff	66%	68%	94%	75%	77%	17%
Enrollment	Total enrollment (12-month)	5190.0	1257.0	95%	214.2	0.0	99%
	YOY change, 12-month enrollment	3%	0%	92%	-38%	-58%	94%
	Undergraduate/total enrollment	87%	100%	93%	97%	100%	44%
	Enrollment 10% lower than 5-year high	41%	0%	94%	93%	100%	99%
	3 consecutive years of >5% enrollment drops	3%	0%	94%	21%	0%	93%
County Controls	Population (mil)	1.1	0.4	92%	1.5	0.8	96%
	Personal income per capita ($)	46670.8	42450.0	92%	52095.9	47541.0	96%
	Unemployment rate	1%	0%	95%	0%	0.1	99%
	Poverty rate	15%	14%	93%	14%	0.1	97%
	# of Observations			110,559			1,263

Source: Authors' calculations based on IPEDS data and PEPS Closed School Reports, 1996-2023

Notes: Number of observations reflects the 2002-2023 sample; many covariates are missing at much lower rates for the subsample used for some of the analysis (2006-2020). Examples include the financial responsibility composite score and financial data. Never-closed institutions are included in the sample each year they reported being in operation. The 1,263 closed institutions are observed once, 2 years before closure, because the data is predominantly missing in the year of closure.