NBER WORKING PAPER SERIES

PREDICTING COLLEGE CLOSURES AND FINANCIAL DISTRESS

Robert J. Kelchen
Dubravka Ritter
Douglas A. Webber

Working Paper 33216
http://www.nber.org/papers/w33216

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2024

The views expressed here are those of the authors and do not necessarily reflect the views of the Board of Governors of the Federal Reserve, the Federal Reserve Bank of Philadelphia, the Federal Reserve System, or the National Bureau of Economic Research. No statements here should be treated as legal advice. The authors thank John Campbell, Julia Cheney, Robert Hunt, and Jeff Larrimore for helpful comments. We also gratefully acknowledge excellent research support by Akash Banerjee and Jacob Goldsmith. All remaining errors are our own.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

Predicting College Closures and Financial Distress
Robert J. Kelchen, Dubravka Ritter, and Douglas A. Webber
NBER Working Paper No. 33216
November 2024
JEL No. I2, I22, I23

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 to 2023. We provide an extensive description of what is known and unknown about closed colleges compared with institutions that did not close. Using this data, we first develop a series of predictive models 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 that 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 far more effective at predicting college closures than linear probability models, and considerably more effective than existing accountability metrics. Our preferred model, which combines an off-the-shelf machine learning algorithm with the richest set of explanatory variables, can significantly improve predictive accuracy even for institutions with complete data, but is particularly helpful for predicting instances of 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.

Robert J. Kelchen
University of Tennessee, Knoxville
325 Bailey Education Complex
1126 Volunteer Boulevard
Knoxville, TN 37996
rkelchen@utk.edu

Douglas A. Webber
Federal Reserve Board
20th St and Constitutional Avenue, NW
Washington, DC 20511
douglas.a.webber@frb.gov

Dubravka Ritter
Consumer Finance Institute
Federal Reserve Bank of Philadelphia
10 Independence Mall W
Philadelphia, PA 19106
dubravka.ritter@phil.frb.org

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 the post-pandemic recovery. For this reason, measuring and predicting financial distress for these institutions is more important than ever. Yet this endeavor is difficult owing 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 percent from 2010 to 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 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 percent to 62 percent 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 increased 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 percent 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 owing 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 financial distress — up to and including 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 emergency actions taken to freeze or reduce personnel costs (Natow, 2021). However, the withdrawal of pandemic-era federal funding, along with existing stressors, likely resulted in an increase in closures during 2023 (Sanchez, 2024) and into 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). But 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 on economic activity 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 assemble 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 monitoring solution to predicting the financial distress and closure of institutions — at least at the federal level — is to provide straightforward and intuitive financial performance metrics that are correlated with closure. These federal performance metrics represent helpful but suboptimal measures for purposes of predicting closures for two reasons: data availability and predictive accuracy. We document a high degree of missing data among colleges that 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 but can only deliver on their predictive accuracy promises if used judiciously and with the full set of available data instead of selected (key) metrics.

For instance, consider three distinct models predicting closure: (1) an OLS model that includes only federal accountability metrics combined with sector and year controls, (2) an OLS model that includes a broader set of financial data and other controls in binned form (to accommodate missing values), and (3) a machine learning model that has the capability of addressing missing data while utilizing 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 percent of the 100 institutions with the highest predicted likelihood of closing actually closed within three years using the federal metrics model, whereas 61 percent of institutions actually closed within three years using the OLS model with additional binned controls and 84 percent of institutions actually closed within three years using the machine learning model. We further illustrate the benefits of using our models and data to assess closure predictions in more local geographic areas, like states, while urging analysts to carefully consider measures of predictive accuracy before doing so. 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). While college closures have a long history in America (Tewksbury, 1932), many colleges are resilient and manage to avoid closure against difficult odds. An analysis of nearly 500 private nonprofit colleges that were identified as having limited resources in 1972 found that nearly 85 percent of the institutions continued to operate in some form four decades later (Tarrant et al., 2018). Public higher education systems, in particular, rarely suffer closures because of 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 shares 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 the 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 often focus on colleges' role in preparing students for the labor market. Students rate economic factors among the most important reasons for going to college (e.g., Stolzenberg et al., 2020), and a growing number of states explicitly tie 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).

A sizable body of research shows a strong relationship between the availability of higher education opportunities in a local community and economic health, emphasizing the importance of colleges as anchor institutions along with medical institutions (e.g., Birch et al., 2013; Harkavy & Zuckerman, 1999; Harker et al., 2022; Harris & Holley, 2016). 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). The presence of colleges leads to higher levels of educational attainment and employment in human capital-intensive industries, more patents, increased economic mobility, and increased local economic output (Andrews, 2023; Carlino & Hunt, 2009; Howard et al., 2022; Lehnert et al., 2024; Russell & Andrews, 2022; Russell et al., 2022).

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 because of 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 3 million employees. In the following section, we discuss key revenue and expenditure categories and the implications for institutional finances.

a. Revenues

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. Owing to both the business cycle and the 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.

Figures 1a–1c depict trends in key revenue categories by institutional sector from 2002 to 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 owing 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 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 from 2008 to 2009 and again from 2021 to 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 with public colleges, while investment returns are far more influential owing 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 90 percent of their funding from tuition and fees over the past two decades. Second, revenue tripled from $15 billion to $46 billion from 2002 to 2011 as the for-profit sector grew 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 prices.

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 revenue 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 percent 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). However, the mechanism used to allocate funding (such as by enrollment or performance) matters far less than the amount of funding (Kelchen et al., 2024a; Ortagus et al., 2020).

States allocate approximately 90 percent 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). 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, especially vulnerable to declines in resources and tuition increases as enrollment increases during recessionary periods of reduced state funding (Barr & Turner, 2013; Rosinger et al., 2022). 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.

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 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 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 revenue in the 2021–22 fiscal year (USA Today, 2024), but many Division I institutions still rely on student fees and institutional contributions 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 percent of all endowment assets in American higher education. Going further, five institutions held 25 percent 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 percent to 5 percent 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 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 owing 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 members 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 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 percent and 30 percent 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).

The construction of the instructional expenditures category in IPEDS is relatively narrow, excluding key functions such as advising (classified under academic support), student services, and information technology (which can fall under multiple functional categories, depending on how an institution allocates expenses). These three categories represent just under one-fourth of all spending at public institutions but 60 percent 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 that is collected annually on the academic year calendar for each UnitID (an 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 two-year (or less), public four-year (or more), private nonprofit two-year (or less), private nonprofit four-year (or more), private for-profit two-year (or less), and private for-profit four-year (or more). Considering the predominant degree classification better reflects the institutions' focus, since the highest degree offered would often classify community colleges that offer a single, small B.A. program as four-year institutions. About one-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 the 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 interest, debt,, and amortization (EBIDA); debt to EBIDA; debt to assets (leverage); change in debt to assets
- Other derived measures: 10 percent decline in revenue relative to high in the last five years; persistent negative operating margin (at least three of the past five years); 10 percent decline in enrollment relative to high in the last five years; 5 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., an 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 percent 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 the FSA OPEID levels is a complex endeavor as 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 the FSA. For example, Indiana University and University of Wisconsin

[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 10 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 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.

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).

We meticulously aggregate all 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 analytic 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 10 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 the 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 informative. 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 from 1996 to 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 two-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 from 2016 to 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 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 to address financial distress among public institutions, more often than not, it will be mergers or consolidations that are presented as the remedy, not closure. This is in part because closing a public college is a deeply political decision, similar to closing a military base. 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.

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 7 percent during this time period).

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 percent 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.

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 1 million students during our panel who attended colleges that closed two years later. The vast majority of students affected by closures were enrolled in the 2010s.

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 percent 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.

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.

IV. Methodology

A. Identifying Predictors of Financial Distress

We implement 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. Our work builds 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.

Classification algorithms such as XGBoost are designed to handle large amounts of incomplete data and are capable of incorporating complex interactions and nonlinear relationships. They are thus likely to be better suited for predicting rare events like college closures or financial distress compared with traditional linear probability estimation or compared with extant score-based accountability metrics (we directly test this hypothesis below).[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. 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.

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:

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

where Y_{it} is an outcome variable denoting either closure or a measure of financial distress (10 percent enrollment decline relative to five-year high, 10 percent revenue decline relative to five-year high, three 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.

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

[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 the other metrics of financial distress, as well.

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 continuous values and because linear relationships between the likelihood of closures and measures such as enrollment, staff, or revenue 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 the "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 high 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 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.

To compare the performance of these predictive models, we split our observations into 75 percent training data and 25 percent 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] The 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. A higher AUC implies that the model is more successful at correctly classifying the binary outcome. An

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 theory, each subsequent model could 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. Assessing Potential 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 closure 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,

AUC of 0.5 essentially means that the model is no better than random chance, while models with AUCs in excess of 0.8 or 0.9 are considered highly effective at correctly classifying the outcome.

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 in 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 will not ultimately close) and false negatives (institutions at moderate 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 accuracy 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 15 percent from 2025 to 2029. These effects would be concentrated locally and regionally based on declines in college-age populations resulting from changes in migration and fertility rates, 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 percent from 2025 to 2029 come to pass, considering two potential manifestations:
    a. A one-time 15 percent drop in enrollment, with no further declines but a permanently lower level of enrollment, and
    b. An annual enrollment decline such that the aggregate enrollment decline reaches 15 percent by 2029.

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. This likely results in a conservative estimate of the number of closures because of the presence of fixed costs such as facilities and tenured faculty at many institutions.

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 in two ways: as "closed in year *t*" and as "closed within 3 years of year *t*." The two measures are complementary; one can imagine circumstances in which predicting the specific year of closure may be desirable, but "closing soon" may be sufficient in others. Ex ante, we suspect that 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.

Again, owing 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 two-year and three-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 five 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.

As shown in **Table 5**, with AUCs approaching or in excess of 80 percent, 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 percent 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 AUCs 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 2,990 institution-year observations, which represents only 15 percent of the available sample, owing to the prevalence of the missing data. So, although the AUC is a respectable 78.7 percent, the model predicts only 16 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 like in the previous specification. This increases the sample size slightly, improves the AUC to a magnitude comparable to the XGBoost models (83.4 percent), and increases the number of predicted closures to 35, yet this is still far from the actual number of closed institutions of 335 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 (20,596, because some observations still get dropped owing to unexpected missing values), such that the model predicts a more on-target 327 closures. However, the predictive accuracy drops to 75.6 percent, meaning that the model discriminates less well because of the implicit imputation inherent in using the binning method. We also note that the OLS-based

AUCs are more unstable and vary more — often significantly outperforming XGBoost, even with the use of LASSO — with relatively minor changes in the sample period than XGBoost AUCs.

In the row that follows, we show that using the XGBoost model on the same binned controls as the OLS improves predictive accuracy to an AUC of 76.9 percent and allows us to consider the full sample of 20,596 institution-year observations in the evaluation data. For that same sample, XGBoost does even better using continuous versions of the binned controls (an AUC of 80.6 percent), and better still using the fullest available set of covariates including 4th and 5th lags, county controls, institutional features, and even richer financial metrics (an AUC of 81.8 percent).

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. Conditional on targeting the same AUC of about 79–80 percent, 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 (a higher AUC for same sample relative to linear probability) or reliability when some of the data is missing (the same AUC on a larger sample of institutions). The tradeoff is that these methods can be rather data-intensive and may require more training for the analyst, which may limit their use in certain contexts.

Also, in the upper panel of **Table 5**, we provide comparable estimates considering "closed within three 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 86.8 percent 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 some of the following sections, while generally preferring a definition of closure with a longer time window because of its promising improvement in predictive performance.

To benchmark our models against existing methods, in the lower panel of **Table 5**, we provide estimates of predicted number of closures and AUCs 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 AUCs and in terms of number of institutions with predictions (and therefore total number of predicted closures), and especially for the definition of closure as "closed within three years."

With an AUC of 88.6 percent, the XGBoost with the richest controls significantly outperforms even the 79.5 percent AUC of the XGBoost on the federal metrics. That said, we note that the FRC score does have predictive power, even controlling for all 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 three years), while the XGBoost model performs much better with the alternate closure definition on the better populated 2006–2020 data than on the 2002–2023 data. Reassuringly, our preferred model is most predictive for institutions whose closures are likely to be more impactful to their local economies, namely larger institutions (featuring near-perfect predictive accuracy for institutions with more than 5,000 students) and four-year institutions.

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 three 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 percent 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 three 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 (not shown in the figures). Some 84 percent of the 100 institutions with the highest predicted probability of closure actually closed within three years, compared with 47 percent for the federal metrics model and 61 percent for OLS with binned controls.

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, although 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.

Consistent with our AUC measures, the machine learning model has lower false negative rates at moderate thresholds, as shown in **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 it 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 (over 16,000 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 nonsensical 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 it argues for the inclusion of recent trajectory as an important metric that should be considered by monitoring agencies in addition to absolute levels, but it 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. First, year fixed effects are much more important predictors in the OLS models; our preferred models do not include year fixed effects because of their limited utility in this context.[6] Nevertheless, we estimated our models with year fixed effects (not shown) and found them to be marginal contributors to predictive accuracy only for the linear models but not predictive in the machine learning models. For the XGBoost models, which allow for more complex interactions and nonlinear relationships, it is the underlying metrics (e.g., financial conditions) that are of greater relative importance. In OLS models, it is more common for the model to imply "there is something about a particular year that is important, but we don't know what it is," while machine learning models can better identify which underlying metrics are actually important. That said, even XGBoost models indicate that a portion of closure propensity for private nonprofit four-year institutions cannot be captured very well by the observables.[7] This speaks to idiosyncratic, unobservable factors — like governance — likely

[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.

[6] In any predictive model, future time fixed effects (e.g., the knowledge of whether a given year had many or few aggregate closures, all else equal) are unknown. To put it differently, year effects may be useful in predicting past closures, but not future ones.

[7] For the most recent years of data, the CARES Act funding to colleges and universities affected smaller PNFP four-year institutions in particular, so the sector dummy is likely picking up some of the effect of that funding on

having a role in closures of these institutions. On the other hand, 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. Importantly, this increase in performance is due to richer institution-level covariates and not county-level controls; county-level covariates appear quite low in the feature importance lists for the XGBoost model with the richest controls. XGBoost models omitting those county-level controls perform just as well as those considered in Table 5.

We note that these key predictors are intended to be illustrative and should not be used outside of this methodology with the expectation of comparable predictive accuracy. They are helpful in understanding the qualitative differences between the models and the performance improvements machine learning methodologies brings to the table by using a longer time series of richer data with a more flexible estimation. In other words, the improvements in predictive power we present are only possible because we (1) assembled a long time series, (2) collected and synchronized a large number of variables, and (3) used a machine learning model. We recognize that this combination of data and methodological choices renders our methodology more complex and time-consuming to adopt compared with focusing on a small number of commonly used metrics.

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 with 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 percent 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 actual closures in the 2002–2023 evaluation dataset, the XGBoost model predicts very few institutions accurately, and the

financial solvency of smaller institutions. This might mean that enrollment changes are a better harbinger of doom for those types of institutions than financials because financials effectively have an error term incorporated in certain circumstances.

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 35 closed institutions, or some one in 10 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 percent, 60 percent, 70 percent, or 80 percent of true positives?[8] 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 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 (the percent of total institutions that did not close but were predicted to close) for the best-performing model,

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

XGBoost, ranges from 12 percent in the full sample with a true positive rate of 51 percent, to 51 percent when the true positive rate is 92 percent. In other words, a regulator would have to screen only one-tenth of institutions in order to detect half of true closures, but a full half of institutions in order to detect 92 percent of true closures — even for institutions with (some) missing data. Screening about one-third of institutions (a false positive rate of 33 percent) with XGBoost would detect over 80 percent of true closures (a true positive rate of 82 percent), 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 percent of institutions owing 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 percent or more closures, the model with all controls would have a false positive rate of 51 percent and the federal metrics model 55 percent. Finally, using the LASSO OLS produces clearly inferior results in this exercise. Because the model cannot provide a prediction of any kind for the 92 percent 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 8 percent, 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 the non-missing sample, and (b) the XGBoost algorithm compared with the linear probability models, and (c) the full available metrics compared with the federal metrics.

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 owing 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 nonprofit four-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 only federal data 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 owing 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 7 percent.

F. *Predicting Closures in Smaller Geographic Areas*

While producing national-level estimates of predicted closures is a worthwhile exercise, it may be in the interest of regional, state, and other authorities to monitor closures more locally. To do this effectively, the analyst must be sure to assess the predictive accuracy of the model(s) in the specific geographic area studied. To illustrate the potential benefits — and to warn of potential pitfalls — associated with predicting college closures at sub-national levels, we use our predicted closure probabilities to assess predictive accuracy of our preferred model for each of the states in the U.S. In **Figure 9**, below, we display the AUCs at the state level, calculated from a model that pools observations across states. We note that the state-level AUC values range from effectively a coin toss (an AUC of 51 percent in Montana) to near-perfection predictions (an AUC of 99 percent in Connecticut). Of the states with at least one closure during our sample period that are included in **Figure 9** (i.e., for which it is possible to test the model's accuracy), about two-thirds have an AUC in excess of 70 percent, which is generally considered strong. Those states with the weakest AUCs are typically either quite small (so it is difficult to achieve predictive accuracy for sample size reasons) or have particularly idiosyncratic private higher education environments (e.g., Wisconsin). Comparable methodology could be used — again, with appropriate precautions and after carefully evaluating the predictive power of the models for the selected sample — to study specific sub-sectors or institutions of special interest.

To further illustrate the potential usefulness of our methodology for state-level closure predictions, we compare time-specific measures of actual closures and predicted closures (calculated as a sum of college-level predicted probabilities in each state and year) in **Figure 10**. Not surprisingly, our predictions match actual closures best in states with higher AUCs and perform reasonably well in nearly all states with large numbers of closures (e.g., California, Florida, Illinois, Missouri, New York, Pennsylvania, Tennessee, Texas). Notably, our model predicted an increase in closures within three years in the post-pandemic period, which is consistent with the recently observed uptick in the number of institutions announcing or considering closure or other severe fiscal measures.

Theoretically, analysts could develop predictive models that are specific to a particular segment or geography, assuming data availability and sample sizes allow such a pursuit. We note that our prior caution regarding using college-and-year level predicted probabilities to identify *individual institutions* at risk of closure remains, even if the model is developed specifically for a particular segment or local area. In most cases, the majority of institutions with elevated predicted probabilities for closure represent false negatives.

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 nonprofit and for-profit colleges. In other words, we are making the assumption that no public institutions will (be allowed to) close. **Table 8** presents the predicted number of students, faculty, staff, and expenses that would be predicted to be affected by the continuous LASSO model, should these additional closures occur.

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), column (1) shows that we can expect to see an additional 1.0 closures per year (an increase of 2 percent over the average annual closures). To assess how the demographic cliff might impact closures, we consider two types of potential enrollment changes — a one-time 15 percent drop (with permanently lower enrollment), presented in column (2), and a "downward-sloping hill" of enrollment in column (3). In other words, under the last scenario, enrollments would decline gradually over time as large, older cohorts of students are successively replaced by smaller, younger cohorts. This process may take a decade or more to fully play out in reality, but we consider a worst-case scenario of it materializing over five years in our analysis. The thought exercise we conduct here with respect to the prospective enrollment changes due to external factors such as the demographic cliff is how many additional *annual* closures we might expect once the demographic changes have fully phased in; the cumulative effect would represent a multiple of these additional annual closures.

Assuming the worst-case scenario predictions come to pass from the upcoming demographic cliff (or a 15 percent decline in enrollment), there could be as many as 80 (142 percent of the average annual closures) additional closures. On the other hand, a gradual decrease in enrollment equivalent to the demographic cliff would result in a predicted annual increase in the rate of closures of 4.6 (an increase of 8.1 percent over the average annual closures). Looking instead at a measure of severe financial distress (not reported), 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.

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 the 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, although 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 and medium-size communities, and often act as anchor institutions in those communities.

Even ignoring the potential negative effects due to reduced training capacity in a county that 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 services). Moreover, most students work while attending college, so any working students who are either attracted to or kept from leaving the community because of the presence of the educational 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 because of 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 to 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 models 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, to 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, which accommodate missing data more flexibly than even elaborate binning or other linear imputation methods.

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 — that 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 significant 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 percent of colleges actually closed within three years. The methods we outline may also be useful to various levels of government preparing for sector-level disruptions and their subsequent economic fallout, but we caution that our data and models should be used cautiously for more localized geographic areas (the state level or smaller), with due attention paid to metrics of predictive accuracy like AUCs and false/negative rates for the specific area studied. Indeed, our results suggest that local communities may be able to anticipate and prepare for labor market and infrastructure disruptions if an increase in aggregate college closings appears imminent and be prepared to use whatever levers available to support affected community members and businesses during the transition.

REFERENCES

Ambrose, C. M., & Nietzel, M. T. (2024). *Colleges on the brink: The case for financial exigency.* Rowman & Littlefield.

American Council of Trustees and Alumni (2021). *The cost of excess: Why colleges and universities must control runaway spending.*

American Council on Education (2014). *Understanding college and university endowments.*

Andrews, M. J. (2023). How do institutions of higher education affect local invention? Evidence from the establishment of US colleges. *American Economic Journal: Economic Policy, 15*(2), 1-41. https://doi.org/10.1257/pol.20200320.

Archibald, R. B., & Feldman, D. H. (2008). Explaining increases in higher education costs. *Journal of Higher Education, 79*(3), 268-295. https://doi.org/10.1080/00221546.2008.11772099.

Arena, M. L. (2013). The crisis in credit and the rise of non-credit. *Innovative Higher Education, 38*, 369-381. https://doi.org/10.1007/s10755-012-9249-5.

Ashley, A., Loh, C. G., Durham, L., Kim, R., & Bubb, K. (2023). Identifying plan perceptions: Higher education institutions as arts and cultural anchors. *Urban Affairs Review, 59*(5), 1496-1529. https://doi.org/10.1177/10780874221108103.

Barr, A., & Turner, S. E. (2013). Expanding enrollments and contracting state budgets: The effect of the Great Recession on higher education. *ANNALS of the American Academy of Political and Social Science, 650*(1), 168-193. https://psycnet.apa.org/doi/10.1177/0002716213500035.

Barr, A., & Turner, S. (2015). Out of work and into school: Labor market policies and college enrollment during the Great Recession. *Journal of Public Economics, 124*, 63-73. https://doi.org/10.1016/j.jpubeco.2014.12.009.

Bates, L. J., & Santerre, R. E. (2000). A time series analysis of private college closures and mergers. *Review of Industrial Organization, 17*, 267-276. https://doi.org/10.1023/A:1007898402967.

Baum, S., & Lee, V. (2018). *Understanding endowments.* Urban Institute.

Baumol, W. J. (1967). Macroeconomics of unbalanced growth: The anatomy of urban crisis. *American Economic Review, 57*(3), 415-426. https://www.jstor.org/stable/1812111.

Birch, E., Perry, D. C., & Taylor, Jr., H. L. (2013). Universities as anchor institutions. *Journal of Higher Education Outreach and Engagement, 17*(3), 7-15.

Bowen, H. R. (1980). *The costs of higher education: How much do colleges and universities spend per student and how much should they spend?* Jossey-Bass.

Bransberger, P., Falkenstern, C., & Lane, P. (2020). *Knocking at the college door: Projections of high school graduates.* Western Interstate Commission for Higher Education.

Brenan, M. (2023, July 11). Americans' confidence in higher education down sharply. *Gallup*. https://news.gallup.com/poll/508352/americans-confidence-higher-education-down-sharply.aspx.

Britton, T., Rall, R. M., & Commodore, F. (2023). The keys to endurance: An investigation of the institutional factors related to the persistence of historically Black colleges and universities. *Journal of Higher Education, 94*(3), 310-332. https://doi.org/10.1080/00221546.2022.2082786.

Burke, L. (2024, January 24). Penn State plans nearly $100M in cuts for FY26 budget. *Higher Ed Dive.* https://www.highereddive.com/news/penn-state-cuts-budget-2026/705542/.

Burns, R., Brown, L., Heckert, K., Weeden, D., Kim, H. S., Randolph, B., Pevitz, A., Karamarkovich, S., & Causey, J. (2023). *A dream derailed? Investigating the impacts of college closures on student outcomes.* State Higher Education Executive Officers Association.

Carlino, G., & Hunt, R. (2009). What explains the quantity and quality of local inventive activity? *Brookings Papers on Economic Activity, 2009*, 65-123.

Celli, V., Cerqua, A., & Pellegrini, G. (2023). The long-term effects of mass layoffs: Do local economies (ever) recover? *Journal of Economic Geography, 23*(5), 1121-1144. https://doi.org/10.1093/jeg/lbad012.

Cellini, S. R., & Goldin, C. (2014). Does federal student aid raise tuition? New evidence on for-profit colleges. *American Economic Journal: Economic Policy, 6*(4), 174-206. https://doi.org/10.1257/pol.6.4.174.

Chakrabarti, R., Gorton, N., & Lovenheim, M. F. (2020). *State investment in higher education: Effects on human capital formation, student debt, and long-term financial outcomes of students.* Federal Reserve Bank of New York Staff Reports 941.

Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939785

Colby, G. (2023). *Data snapshot: Tenure and contingency in US higher education.* American Association of University Professors.

Commonfund Institute (2023). *Commonfund higher education price index.*

Conzelmann, J. G., Hemelt, S. W., Hershbein, B. J., Martin, S., Simon, A., Stange, K. M. (2023). Grads on the go: Measuring college-specific labor markets for graduates. *Journal of Policy Analysis and Management*. https://doi.org/10.1002/pam.22553.

Curs, B. R., & Jaquette, O. (2017). Crowded out? The effect of nonresident enrollment on resident access to public research universities. *Educational Evaluation and Policy Analysis, 39*(4), 644-669. https://doi.org/10.3102/0162373717704719.

Curti, M., & Nash, R. (1965). *Philanthropy in the shaping of American higher education*. Rutgers University Press.

Delaney, J. A. (Ed.) (2023). *Volatility in state spending for higher education.* American Educational Research Association.

Delaney, J. A., & Doyle, W. R. (2018). Patterns and volatility in state funding for higher education, 1951-2006. *Teachers College Record, 120*(6), 1-42. https://doi.org/10.1177/016146811812000605.

Deming, D. J., Goldin, C., & Katz, L. F. (2012). The for-profit postsecondary school sector: Nimble critters or agile predators? *Journal of Economic Perspectives, 26*(1), 139-164. https://doi.org/10.1257/jep.26.1.139.

Denison, D., Fowles, J., & Moody, M. J. (2014). Borrowing for college: A comparison of long-term debt financing between public and private, nonprofit institutions of higher education. *Public Budgeting & Finance, 34*(2), 84-104. https://doi.org/10.1111/pbaf.12034.

Denneen, J., & Dretler, T. (2012). *The financially sustainable university.* Bain & Company.

Eide, S. (2018). Private colleges in peril. *Education Next, 18*(4), 34-41. https://www.educationnext.org/private-colleges-peril-financial-pressures-declining-enrollment-closures/.

Enright, M., Lehren, A. W., & Longoria, J. (2020, March 8). Hidden figures: College students may be paying thousands in athletic fees and not know it. *NBC News.* https://www.nbcnews.com/news/education/hidden-figures-college-students-may-be-paying-thousands-athletic-fees-n1145171.

Foote, A., Grosz, M., & Stevens, A. (2019). Locate your nearest exit: Mass layoffs and local labor market response. *ILR Review, 72*(1), 101-126. https://doi.org/10.1177/0019793917753095.

Ginsberg, B. (2011). *The fall of the faculty: The rise of the all-administrative university and why it matters*. Oxford University Press.

Graddy-Reed, A., Feldman, M., Bercovitz, J., & Langford, W. S. (2021). The distribution of indirect cost recovery in academic research. *Science and Public Policy, 48*(3), 364-386. https://doi.org/10.1093/scipol/scab004.

Grawe, N. D. (2018). *Demographics and the demand for higher education.* Johns Hopkins University Press.

Greene, S. (2024, February 7). University of Delaware issues hiring freeze, cites rising health care costs. *WDEL.* https://www.wdel.com/news/university-of-delaware-issues-hiring-freeze-cites-rising-health-care-costs/article_ad710c74-c63b-11ee-ae84-8b2eab190c36.html.

Griffith, A. L., & Rask, K. N. (2016). The effect of institutional expenditures on employment outcomes and earnings. *Economic Inquiry, 54*(4), 1931-1945. https://doi.org/10.1111/ecin.12336.

Harkavy, I., & Zuckerman, H. (1999). *Eds and meds: Cities' hidden assets.* Brookings Institution.

Harker, P. T., Diamond, D., & Reed, D. (2022). *Anchor impact: Understanding the role of higher education and hospitals in regional economies.* Federal Reserve Bank of Philadelphia.

Harris, M. S., & Holley, K. (2018). Universities as anchor institutions: Economic and social potential for urban development. In M. B. Paulsen (Ed.), *Higher education: Handbook of theory and research (Vol. 31)* (pp. 393-439). Springer.

Hillman, N. W., & Orians, E. L. (2013). Community colleges and labor market conditions: How does enrollment demand change relative to local unemployment rates? *Research in Higher Education, 54*, 765-780. https://doi.org/10.1007/s11162-013-9294-7.

Horn, M. B. (2018, December 13). Will half of all colleges really close in the next decade? *Christensen Institute.* https://www.christenseninstitute.org/blog/will-half-of-all-colleges-really-close-in-the-next-decade/.

Hovey, H. A. (1999). *State spending for higher education in the next decade: The battle to sustain current support.* California State Policy Research, Inc.

Howard, G., Weinstein, R., & Yang, Y. (2022). Do universities improve local economic resilience? *Review of Economics and Statistics.* https://doi.org/10.1162/rest_a_01212.

Howard, T. (2014, January 9). How communities can make the most of their anchor institutions. *Governing.* https://www.governing.com/gov-institute/voices/col-communities-local-government-anchor-institutions-democracy-collaborative-dashboard.html.

Jaquette, O., & Curs, B. R. (2016). Creating the out-of-state university: Do public universities increase nonresident freshman enrollment in response to declining state appropriations? *Research in Higher Education, 56*(6), 535-565. https://doi.org/10.1007/s11162-015-9362-2.

Jaquette, O., Curs, B. R., & Posselt, J. R. (2016). Tuition rich, mission poor: Nonresident enrollment growth and the socioeconomic and racial composition of public research universities. *Journal of Higher Education, 87*(5), 635-673. https://doi.org/10.1080/00221546.2016.11777417.

Kelchen, R. (2018). *Higher education accountability.* Johns Hopkins University Press.

Kelchen, R. (2020). *Examining the feasibility of empirically predicting college closures.* Brookings Institution.

Kelchen, R. (2021). An exploration of nonresident student enrollment and institutional finances at public universities. *Journal of Postsecondary Student Success, 1*(1), 81-105. https://doi.org/10.33009/fsop_jpss121539.

Kelchen, R., Ortagus, J., Rosinger, K., Baker, D., & Lingo, M. (2024a). The relationships between state higher education funding strategies and college access and success. *Educational Researcher, 53*(2), 100-110. https://doi.org/10.3102/0013189X231208964.

Kelchen, R., Ortagus, J., Rosinger, K., & Cassell, A. (2024b). Investing in the workforce: The impact of performance-based funding on student earnings outcomes. *Journal of Higher Education, 95*(2), 172-199. https://doi.org/10.1080/00221546.2023.2171201.

Kelchen, R., & Pingel, S. (2024). Examining the effects of tuition controls on student enrollment. *Research in Higher Education, 65*, 70-91. https://doi.org/10.1007/s11162-023-09748-5.

Knox, L. (2023, December 4). Seeking an enrollment Hail Mary, small colleges look to athletics. *Inside Higher Ed*. https://www.insidehighered.com/news/admissions/traditional-age/2023/12/04/small-colleges-bet-new-sports-boost-enrollment.

Kolpin, V., & Stater, M. (2024). The perverse equilibrium effects of state and federal student aid in higher education. *Journal of Economic Behavior & Organization, 217*, 679-691. https://doi.org/10.1016/j.jebo.2023.11.022.

Korn, M. (2024, January 20). This private college has been on its deathbed—for 15 years. *The Wall Street Journal.* https://www.wsj.com/us-news/education/birmingham-southern-college-alabama-aef0fcb7.

Kunkle, K., & Laderman, S. (2023). *State higher education finance: FY 2022.* State Higher Education Executive Officers Association.

Lee, J. (2018). The local economic impact of a large research university: Evidence from UC Merced. *Economic Inquiry, 57*(1), 316-332. https://doi.org/10.1111/ecin.12734.

Lehnert, P., Dell, M., Backes-Gellner, U., & Bettinger, E. (2024). *The effect of postsecondary educational institutions on local economies: A birds-eye view.* Swiss Leading House Economics of Education Working Paper No. 210.

Ma, J., & Pender, M. (2023). *Trends in college pricing and student aid 2023.* College Board.

McClure, K., R., Ryder, A. J., & DeVita, J. M. (2017). Public-private partnerships in college student housing: Lessons from three institutions. *Journal of College & University Student Housing, 43*(2), 72-93.

Moody, J. (2024, March 4). Judge allows Webster to lift endowment restrictions. *Inside Higher Ed*. https://www.insidehighered.com/news/quick-takes/2024/03/04/judge-allows-webster-lift-endowment-restrictions.

National Association of College and University Business Officers (2023). *2022 NACUBO tuition discounting study.*

National Center for Education Statistics (2023). *The condition of education.* U.S. Department of Education.

National Student Clearinghouse Research Center (2024, January 24). *Current term enrollment estimates: Fall 2023.* https://nscresearchcenter.org/current-term-enrollment-estimates/.

Natow, R. S. (2021, March 1). Why haven't more colleges closed? *Chronicle of Higher Education*. https://www.chronicle.com/article/why-havent-more-colleges-closed.

Ortagus, J., Kelchen, R., Rosinger, K., & Voorhees, N. (2020). Performance-based funding in American higher education: A systematic synthesis of the intended and unintended consequences. *Educational Evaluation and Policy Analysis, 42*(4), 520-550. https://doi.org/10.3102/0162373720953128.

Owens, J. (2024, February 2). Cost of weight-loss drugs for state employees hits taxpayers. *Delaware Live*. https://delawarelive.com/cost-of-weight-loss-drugs-hits-taxpayers/.

Parthenon-EY (2017). *Strength in numbers: Strategies for collaborating for a new era in higher education.*

Porter, S. R., & Ramirez, T. J. (2009). *Why do colleges fail? An analysis of college and university closings and mergers, 1975-2005.* Working paper.

Povich, E. S. (2023, December 15). Flagship public universities likely to cut more humanities, staff—especially in rural areas. *Stateline.* https://stateline.org/2023/12/15/flagship-public-universities-likely-to-cut-more-humanities-staff-especially-in-rural-states/.

Redd, K. (2024). *2023 NACUBO-Commonfund study of endowments*. National Association of College and University Business Officers.

Rosinger, K., Kelchen, R., Baker, D. J., Ortagus, J., & Lingo, M. D. (2022). State higher education funding during COVID-19: Lessons from prior recessions and implications for equity. *AERA Open, 8*. https://doi.org/10.1177/23328584221091277.

Russell, L. C., & Andrews, M. J. (2022). *Not the great equalizer? Local economic mobility and inequality effects for the establishment of U.S. universities.* EdWorkingPaper No. 22-634.

Russell, L. C., Yu, L., & Andrews, M. J. (2022). Higher education and local educational attainment: Evidence from the establishment of U.S. colleges. *Review of Economics and Statistics*. https://doi.org/10.1162/rest_a_01214.

Sanchez, O. (2024, January 12). Experts predicted dozens of colleges would close in 2023 – and they were right. *The Hechinger Report.* https://hechingerreport.org/experts-predicted-dozens-of-colleges-would-close-in-2023-and-they-were-right/.

Smith, E. K., Rozek, E. K., & Moore, K. D. (2014). Creating SPOTs for successful aging: Strengthening the case for developing university-based retirement communities using social-physical place over time theory. *Journal of Housing for the Elderly, 28*(1), 21-40. https://doi.org/10.1080/02763893.2013.858091.

Stolzenberg, E. B., Aragon, M. C., Romo, E., Couch, V., McLennan, D., Eagan, M. K., & Kang, N. (2020). *The American freshman: National norms fall 2019.* Higher Education Research Institute, University of California, Los Angeles.

Storms, K., Miller, S. E., & Hall, B. (2017). P4: The role of planning in successful public-private partnerships (P3s). *Planning for Higher Education, 45*(3), 1-13.

Tarrant, M., Bray, N., & Katsinas, S. (2018). The invisible colleges revisited: An empirical review. *Journal of Higher Education, 89*(3), 341-367. https://doi.org/10.1080/00221546.2017.1390971.

Tewksbury, D. G. (1932). *The founding of American colleges and universities before the Civil War, with particular reference to the religious influences bearing upon the college movement.* Teachers College, Columbia University.

USA Today (2024, March 14). *NCAA finances: Revenue and expenses by school.* https://sports.usatoday.com/ncaa/finances.

Ward, J. D., Haynes, M., & Gusakova, S. (2022). *Borrowing during a time of crisis: Examining institutional debt during the Great Recession and COVID-19.* Ithaka S&R. https://doi.org/10.18665/sr.317442.

Webber, D. A. (2016). Are college costs worth it? How ability, major, and debt affect the returns to schooling. *Economics of Education Review, 53*, 296-310. https://doi.org/10.1016/j.econedurev.2016.04.007.

Webber, D. A. (2017). State divestment and tuition at public institutions. *Economics of Education Review, 60*, 1-4. https://doi.org/10.1016/j.econedurev.2017.07.007.

Webber, D. A., & Ehrenberg, R. A. (2010). Do expenditures other than instructional expenditures affect graduation and persistence rates in American higher education? *Economics of Education Review, 29*(6), 947-958. https://doi.org/10.1016/j.econedurev.2010.04.006.

Whistle, W., & Erickson, L. (2019, April 18). *Using instructional spending to test for value in higher ed*. Third Way. https://www.thirdway.org/memo/using-instructional-spending-to-test-for-value-in-higher-ed.

Xu, D., & Ran, F. X. (2020). Noncredit enrollment in community college: Students, course enrollments, and academic outcomes. *Community College Review, 48*(1), 77-101. https://doi.org/10.1177/0091552119876039.

Zapp, M., & Dahmen, C. (2023). Live and (let) die—shifting legitimacies and organizational mortality in American higher education, 1944-2018. *Social Problems.* https://doi.org/10.1093/socpro/spad001.

Zemsky, R., Shaman, S., & Baldridge, S. C. (2020). *The college stress test: Tracking institutional futures across a crowded market.* Johns Hopkins University Press.

Zhang, L., Liu, X., & Hu, Y. (2024). Degrees of return: Estimating internal rates of return for college majors using quantile regression. *American Educational Research Journal*. https://doi.org/10.3102/00028312241231512.

Table 1: Revenues by Institutional Sector, 2021–2022

	Public		Private nonprofit		Private for-profit	
	$	%	$	%	$	%
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.

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.

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 and College Scorecard, 1996–2023

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

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 PEPS Closed School Reports and College Scorecard, 1996–2023

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

Table 5 – Predictive Accuracy for Linear Regression and XGBoost Models, 2002–2021

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	16	78.7%	2,990	32	81.8%	2,062
	Linear Probability - LASSO	Select Continuous	35	83.4%	3,415	59	84.4%	2,353
	Linear Probability	Select Binned	327	75.6%	20,596	1,172	76.2%	18,073
	XGBoost	Select Binned	267	76.9%	20,596	1,073	80.6%	18,073
	XGBoost	Select Continuous	253	80.6%	20,596	1,060	82.8%	18,073
	XGBoost	All	231	81.8%	20,596	1,023	86.8%	18,073
2006-2020	Linear Probability	Federal Metrics	158	76.5%	10,331	586	78.8%	9,107
	XGBoost	Federal Metrics	257	77.4%	16,800	978	79.5%	14,240
	Linear Probability	Select Continuous	16	78.7%	2,990	32	81.8%	2,062
	Linear Probability - LASSO	Select Continuous	35	83.3%	3,414	59	84.4%	2,352
	Linear Probability	Select Binned	291	75.6%	16,800	1,037	77.4%	14,240
	XGBoost	Select Binned	234	78.5%	16,800	940	82.2%	14,240
	XGBoost	Select Continuous	219	81.5%	16,800	930	83.7%	14,240
	XGBoost	All	197	83.1%	16,800	893	88.6%	14,240

Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

Notes: Models estimated or trained on 75 percent of institution-year observations. Predictions and area under the curve (AUC) reported for remaining evaluation observations (25 percent). Closure is measured both as point-in-time (closed in given year) and in a three-year window (closed within three years of current year). There were 342 actual closures (1,091 within three years) in the 2002–2021 sample and 305 (945 within three years) in the 2006–2020 sample.

Table 6 – Key Predictors of Closure and Contribution to Prediction, Select Models, 2002–2021

XGBoost Models					
XGBoost (All Controls)		XGBoost (Continuous)		XGBoost (Binned)	
Covariate	Gain	Covariate	Gain	Covariate	Gain
L2 FRC Score	4.0%	L3 Enroll % change	4.0%	L2 Enroll % change 1stQ	3.2%
L2 Enroll % change	2.4%	L2 OP Margin	4.0%	L3 Revenue % GGC 1stQ	2.6%
L2 Total EAP % change	2.1%	L2 Enroll % change	3.9%	L3 Enroll % change 1stQ	2.5%
L3 Enroll % change	2.0%	L2 Total EAP % change	3.9%	L2 Revenue % GGC 1stQ	2.1%
L2 Revenue % change	1.9%	L2 EAP % Instruction	3.8%	L2 Salaries % Staff 1stQ	2.0%
L4 Revenue % change	1.8%	L2 Revenue % change	3.6%	L2 DCOH 3rdQ	2.0%
PNFP 4yr	1.8%	L3 Revenue % change	3.3%	L2 Total EAP % change 1stQ	1.9%
L2 Staff Total	1.7%	PNFP 4yr	2.9%	L3 Revenue % change 1stQ	1.8%
L3 Revenue % change	1.6%	L2 Expenses % Instruction	2.7%	L2 Revenue % change 1stQ	1.7%
L2 EAP % Instruction	1.6%	L2 EAP % ft	2.6%	L2 Expenses % Interest 1stQ	1.4%
L2 Salaries % Staff	1.6%	L3 OP Margin	2.6%	L3 Total EAP % change 1stQ	1.4%
L2 OP Margin	1.5%	L2 Revenue % Tuition	2.5%	L2 Log Unrestricted Assets 4th	1.4%
L2 Log Unrestricted Assets	1.5%	L3 Expenses % Instruction	2.4%	L3 OP Margin 3rdQ	1.3%
L3 FRC Score	1.3%	L2 Log Unrestricted Assets	2.4%	L2 DCOH 1stQ	1.2%
L5 Revenue % GGC	1.2%	L3 Revenue % Tuition	2.4%	L3 EAP % ft 1stQ	1.1%
L2 DCOH	1.1%	L3 Total EAP % change	2.3%	L2 Debt to Assets 1stQ	1.1%
L2 Revenue % Tuition	1.1%	L3 EAP % Instruction	2.3%	L2 OP Margin 1stQ	1.1%
L4 Expenses % Instruction	1.1%	L2 Log Enroll 12mo	2.0%	L2 Revenue % Tuition 4thQ	1.0%
L2 Expenses % Instruction	1.1%	L3 Log expenses	2.0%	L2 EAP % ft 1stQ	1.0%

Linear Probability Models					
OLS (Binned)			OLS - Lasso (Continuous)		
Variable	Standardized Coeff.	P-Value	Variable	Standardized Coeff.	P-Value
L2 EAP % Instruction 4thQ	0.8%	0.00	L2 DCOH	-4.8%	0.00
L2 DCOH 1stQ	-1.1%	0.00	L3 DCOH	4.5%	0.00
L2 EAP % Instruction 3rdQ	0.7%	0.00	L3 Enroll % change	-0.5%	0.00
L2 Deprec. % Expenses 1stQ	0.7%	0.00	L2 Log expenses	-10.2%	0.00
L2 Log Unrestricted Assets 1stQ	-2.7%	0.00	L2 Expenses % Instruction	-1.3%	0.00
L3 Log Unrestricted Assets 1stQ	2.7%	0.00	L3 Log expenses	9.7%	0.00
L2 Debt to Assets 1stQ	2.9%	0.00	L3 Expenses % Instruction	1.0%	0.00
L2 EAP % Instruction 2ndQ	0.6%	0.00	L2 HCM2 indicator	0.4%	0.00
L2 Log Unrestricted Assets 4thQ	1.2%	0.00	L2 Five % Enroll 3yr	0.4%	0.00
L3 Debt to Assets 1stQ	-2.6%	0.00	L3 Five % Enroll 3yr	0.4%	0.00
L3 Deprec. % Expenses 1stQ	-0.7%	0.00	L2 Total EAP % change	0.3%	0.02
L2 Log Unrestricted Assets 3rdQ	0.8%	0.00	L3 HCM2 indicator	0.3%	0.03
L3 DCOH 1stQ	0.7%	0.00	L3 Ten % Revenue 5yr	0.2%	0.05
L2 EAP % Instruction 1stQ	0.5%	0.00	L3 DBT asst PP change	0.2%	0.05
L2 DCOH 2ndQ	-0.5%	0.00	L2 Revenue % Tuition	0.6%	0.06
L2 Log Unrestricted Assets 2ndQ	0.7%	0.00	L3 Revenue % Tuition	-0.6%	0.06
L3 Revenue % auxiliary 1stQ	0.9%	0.00	L2 Log EBITDA	0.6%	0.08
L3 Deprec. % Expenses 2ndQ	-0.5%	0.00	L3 DCOH change	0.2%	0.09
L3 OP Margin PP change 1stQ	0.5%	0.00	L3 Ten % Enroll 5yr	-0.2%	0.15

Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

Notes: Key predictors identified from models where closure is defined as within three years of evaluation year.

Table 7 – Predictive Power Based on Target True Positive Rate, by Model, 2002–2021

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	305	305	16,495	16,495	50%	0.027	155	51%	51%	150	49%	49%	2,771	17%	17%	0	0%
2002-2023	OLS	Select Binned	342	342	20,254	20,254	50%	0.034	174	51%	51%	168	49%	49%	2,981	15%	15%	0	0%
2002-2023	XGBoost	Select Continuous	342	342	20,254	20,254	50%	0.026	171	50%	50%	171	50%	50%	2,188	11%	11%	0	0%
2002-2023	XGBoost	All	342	342	20,254	20,254	50%	0.021	174	51%	51%	168	49%	49%	2,397	12%	12%	0	0%
2002-2023	OLS LASSO	Select Continuous	26	342	3,389	20,254	50%	0.057	13	50%	4%	13	50%	4%	89	3%	0%	316	92%
2006-2020	XGBoost	Federal Metrics	305	305	16,495	16,495	60%	0.02	186	61%	61%	119	39%	39%	3,996	24%	24%	0	0%
2002-2023	OLS	Select Binned	342	342	20,254	20,254	60%	0.027	213	62%	62%	129	38%	38%	4,317	21%	21%	0	0%
2002-2023	XGBoost	Select Continuous	342	342	20,254	20,254	60%	0.018	206	60%	60%	136	40%	40%	3,472	17%	17%	0	0%
2002-2023	XGBoost	All	342	342	20,254	20,254	60%	0.016	207	61%	61%	135	39%	39%	3,310	16%	16%	0	0%
2002-2023	OLS LASSO	Select Continuous	26	342	3,389	20,254	60%	0.028	16	62%	5%	10	38%	3%	399	12%	2%	316	92%
2006-2020	XGBoost	Federal Metrics	305	305	16,495	16,495	70%	0.017	224	73%	73%	81	27%	27%	5,115	31%	31%	0	0%
2002-2023	OLS	Select Binned	342	342	20,254	20,254	70%	0.018	243	71%	71%	99	29%	29%	6,749	33%	33%	0	0%
2002-2023	XGBoost	Select Continuous	342	342	20,254	20,254	70%	0.015	240	70%	70%	102	30%	30%	5,754	28%	28%	0	0%
2002-2023	XGBoost	All	342	342	20,254	20,254	70%	0.013	248	73%	73%	94	27%	27%	5,593	28%	28%	0	0%
2002-2023	OLS LASSO	Select Continuous	26	342	3,389	20,254	70%	0.015	19	73%	6%	7	27%	2%	719	21%	4%	316	92%
2006-2020	XGBoost	Federal Metrics	305	305	16,495	16,495	80%	0.013	247	81%	81%	58	19%	19%	6,596	40%	40%	0	0%
2002-2023	OLS	Select Binned	342	342	20,254	20,254	80%	0.01	299	87%	87%	43	13%	13%	12,070	60%	60%	0	0%
2002-2023	XGBoost	Select Continuous	342	342	20,254	20,254	80%	0.009	288	84%	84%	54	16%	16%	8,444	42%	42%	0	0%
2002-2023	XGBoost	All	342	342	20,254	20,254	80%	0.01	279	82%	82%	63	18%	18%	6,720	33%	33%	0	0%
2002-2023	OLS LASSO	Select Continuous	26	342	3,389	20,254	80%	0.008	21	81%	6%	5	19%	1%	1,103	33%	5%	316	92%
2006-2020	XGBoost	Federal Metrics	305	305	16,495	16,495	90%	0.007	277	91%	91%	28	9%	9%	9,097	55%	55%	0	0%
2002-2023	OLS	Select Binned	342	342	20,254	20,254	90%	0.006	308	90%	90%	34	10%	10%	13,564	67%	67%	0	0%
2002-2023	XGBoost	Select Continuous	342	342	20,254	20,254	90%	0.006	312	91%	91%	30	9%	9%	10,437	52%	52%	0	0%
2002-2023	XGBoost	All	342	342	20,254	20,254	90%	0.005	315	92%	92%	27	8%	8%	10,299	51%	51%	0	0%
2002-2023	OLS LASSO	Select Continuous	26	342	3,389	20,254	90%	0	26	100%	8%	0	0%	0%	3,389	100%	17%	316	92%

Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

Notes: Models estimated or trained on 75 percent of institution-year observations; predictions reported for remaining 25 percent of observations. Closure is measured within three years of evaluation year.

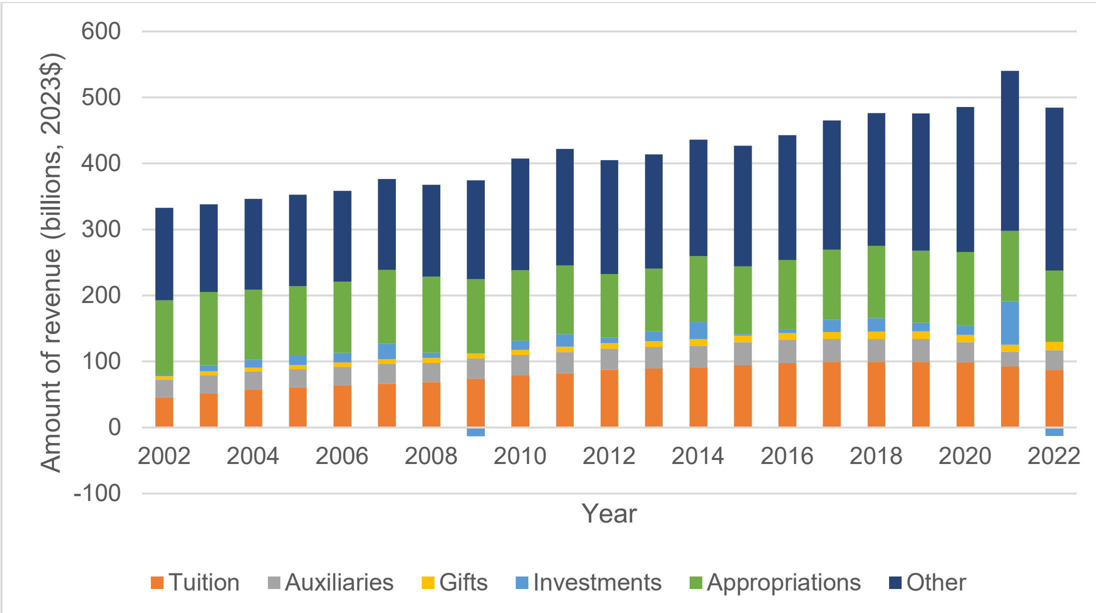
Table 8: Predicted Additional Annual Closures under Selected Scenarios, 2019

	(1) 2019 Enrollment Patterns Continue	(2) Demographic Cliff (one-time, worst-case)	(3) Demographic Cliff (annual, worst-case)
Institutions	1.0	80	4.6
Students	1,263	101,040	7,337
Staff	261	20,880	1,200
Expenses	$15.4m	$1,231m	$70.8m

Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, and College Scorecard, 2002–2023

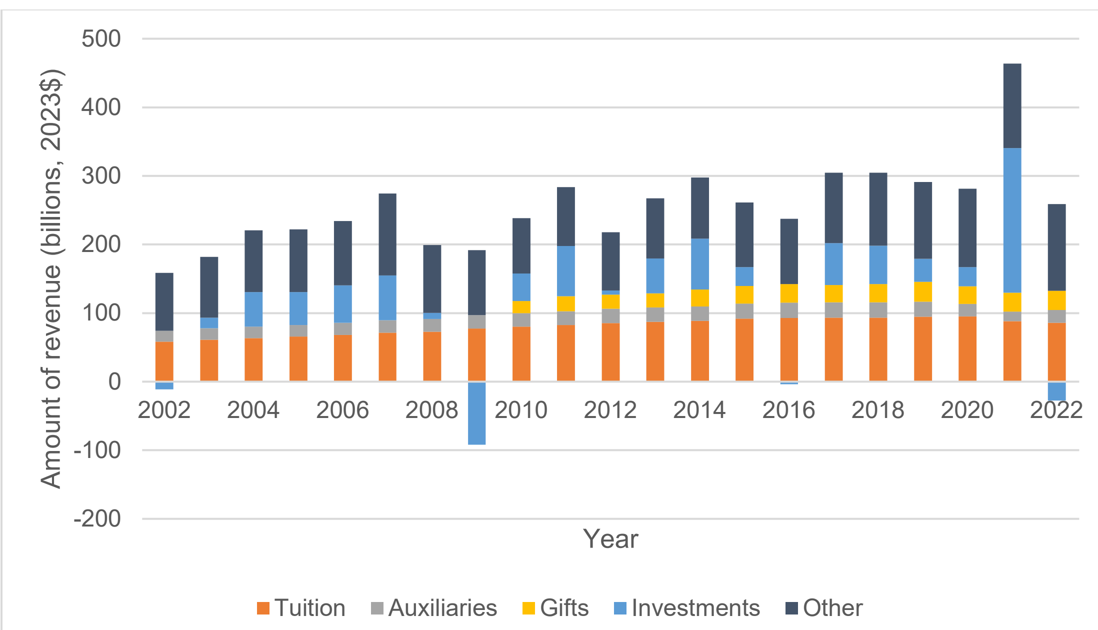
Notes: Predictions are based on the outlined scenarios and predictions from the continuous OLS model with LASSO-selected covariates, scaled up to the full sample of private institutions in the IPEDS data.

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



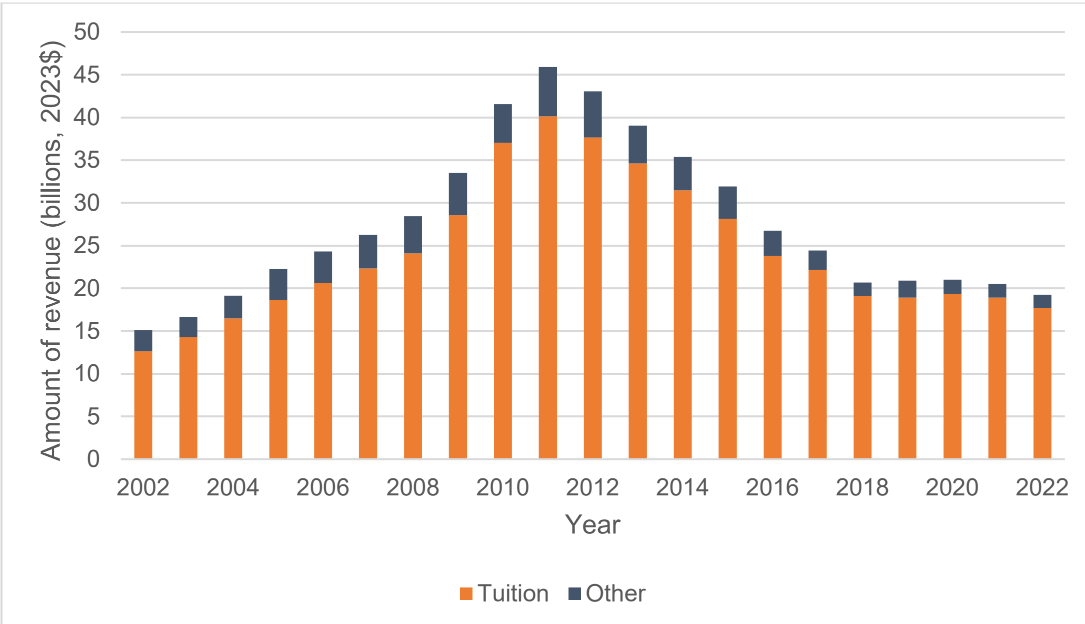
Source: Authors' calculations based on IPEDS data, 2002–2022

Figure 1b: Trends in Sources of College Revenues, Private Nonprofit Institutions, 2002–2022



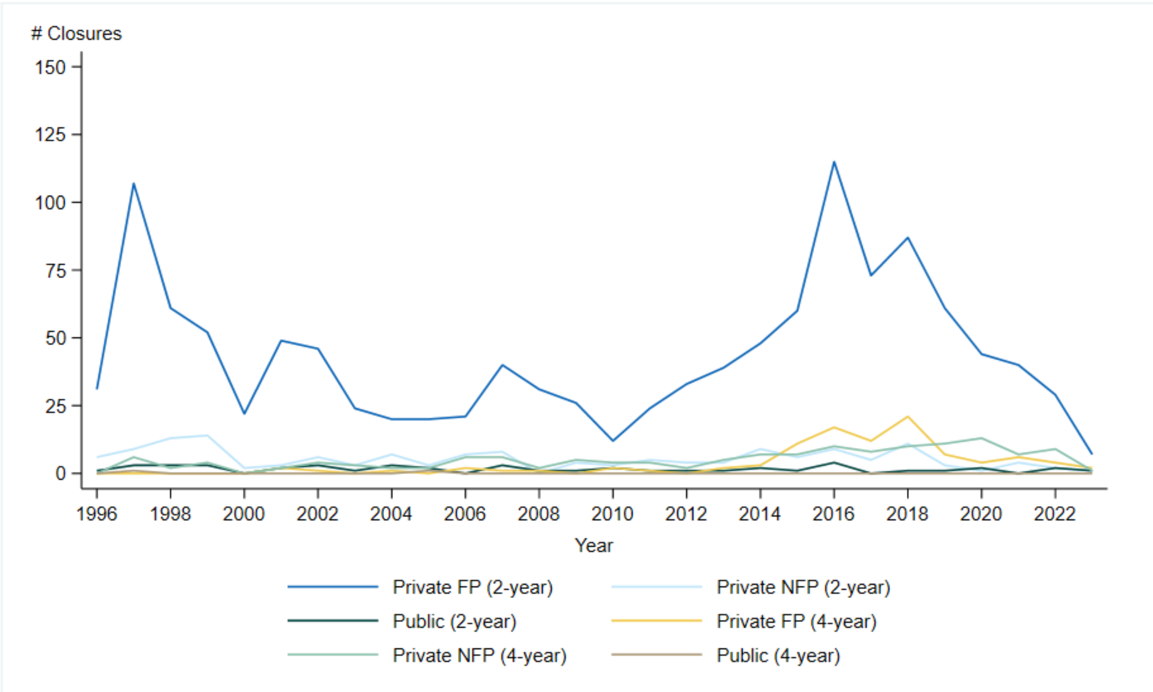
Source: Authors' calculations based on IPEDS data, 2002–2022

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



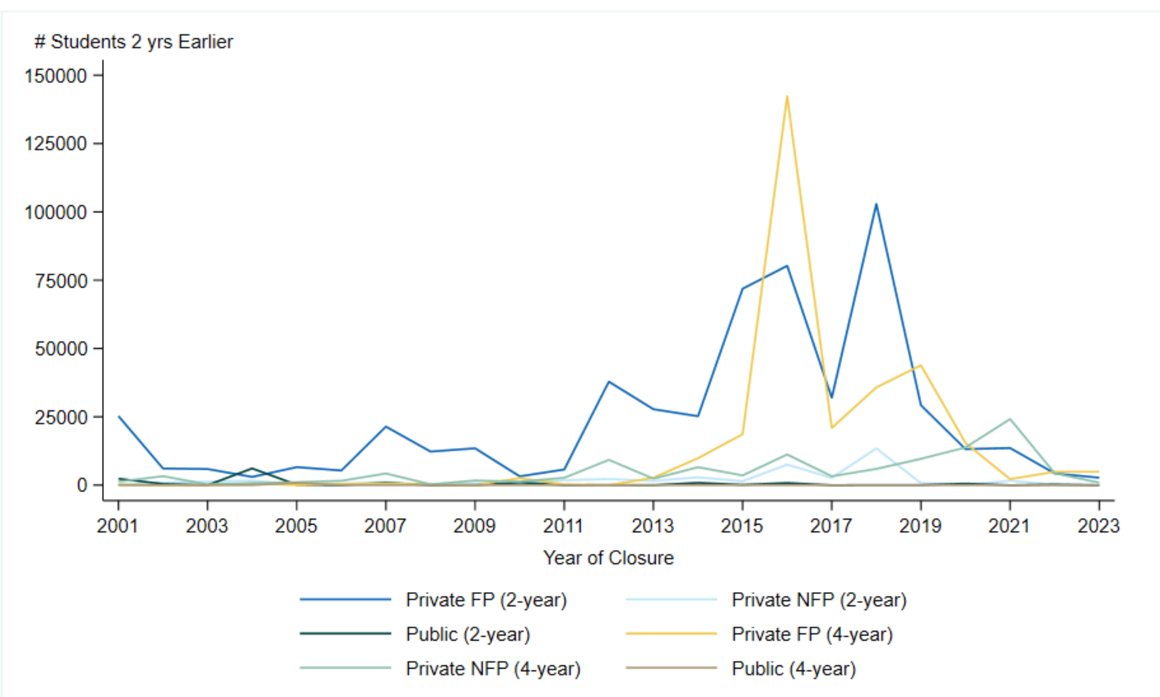
Source: Authors' calculations based on IPEDS data, 2002–2022

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



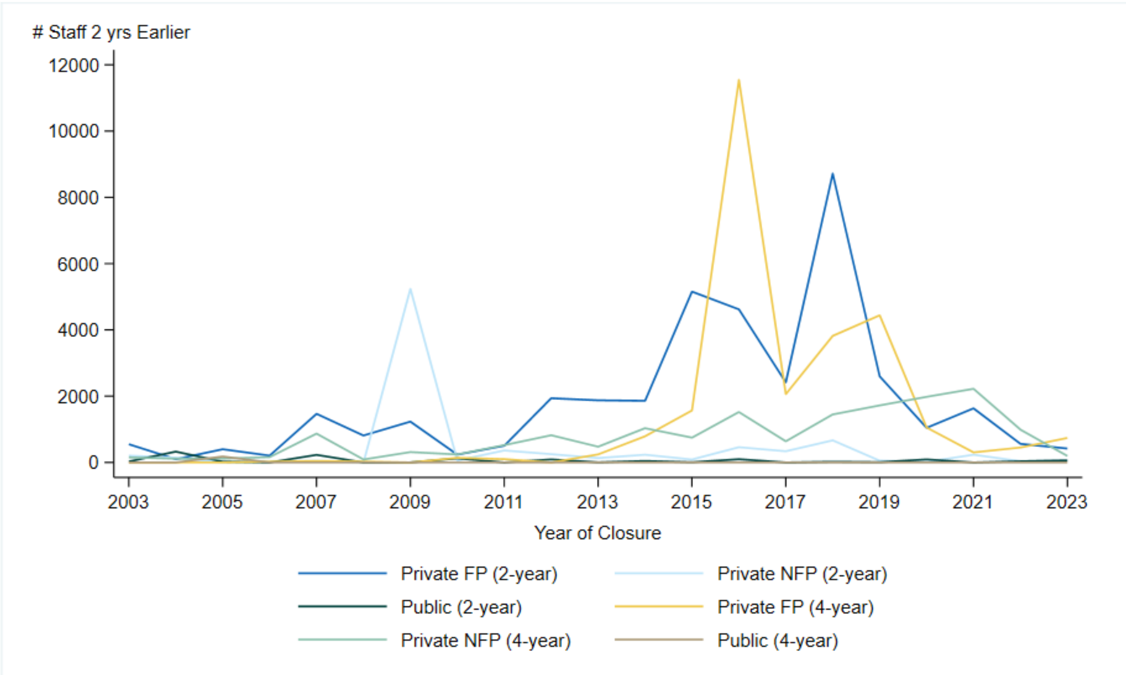
Source: Authors' calculations based on IPEDS, PEPS Closed School Reports and College Scorecard, 1996–2023

Figure 3 – Number of Students Enrolled in Closed Institutions Two Years Prior to Closure, by Institution Type and Year, 2001–2023



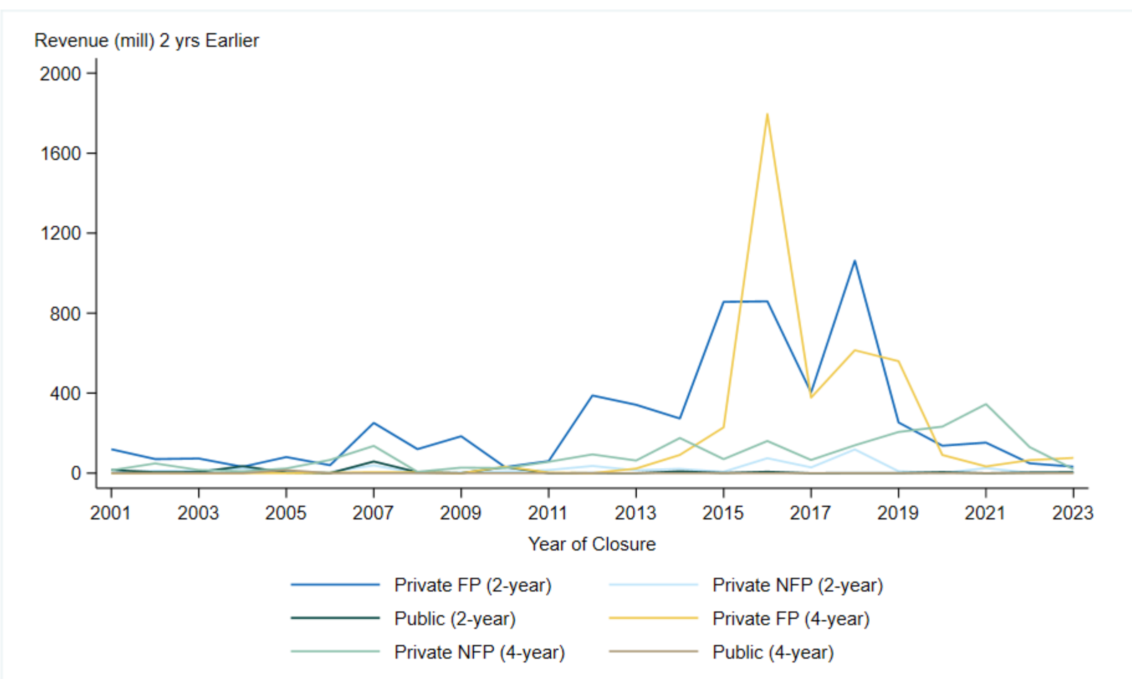
Source: Authors' calculations based on IPEDS, PEPS Closed School Reports and College Scorecard, 2001–2023

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



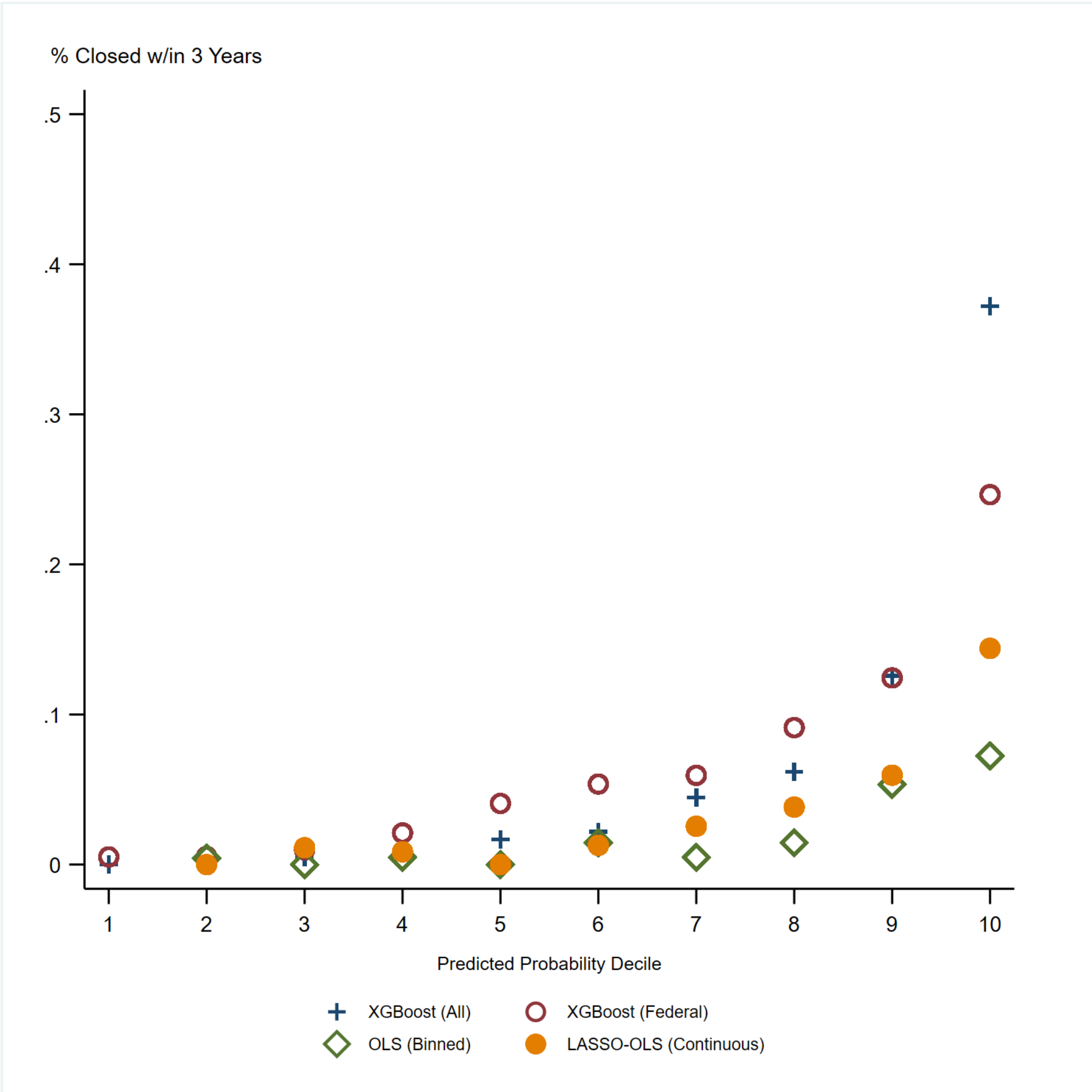
Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, and College Scorecard, 2001–2023

Figure 5 – Total Revenue at Closed Institutions Two Years Prior to Closure, by Institution Type and Year, 2001–2023



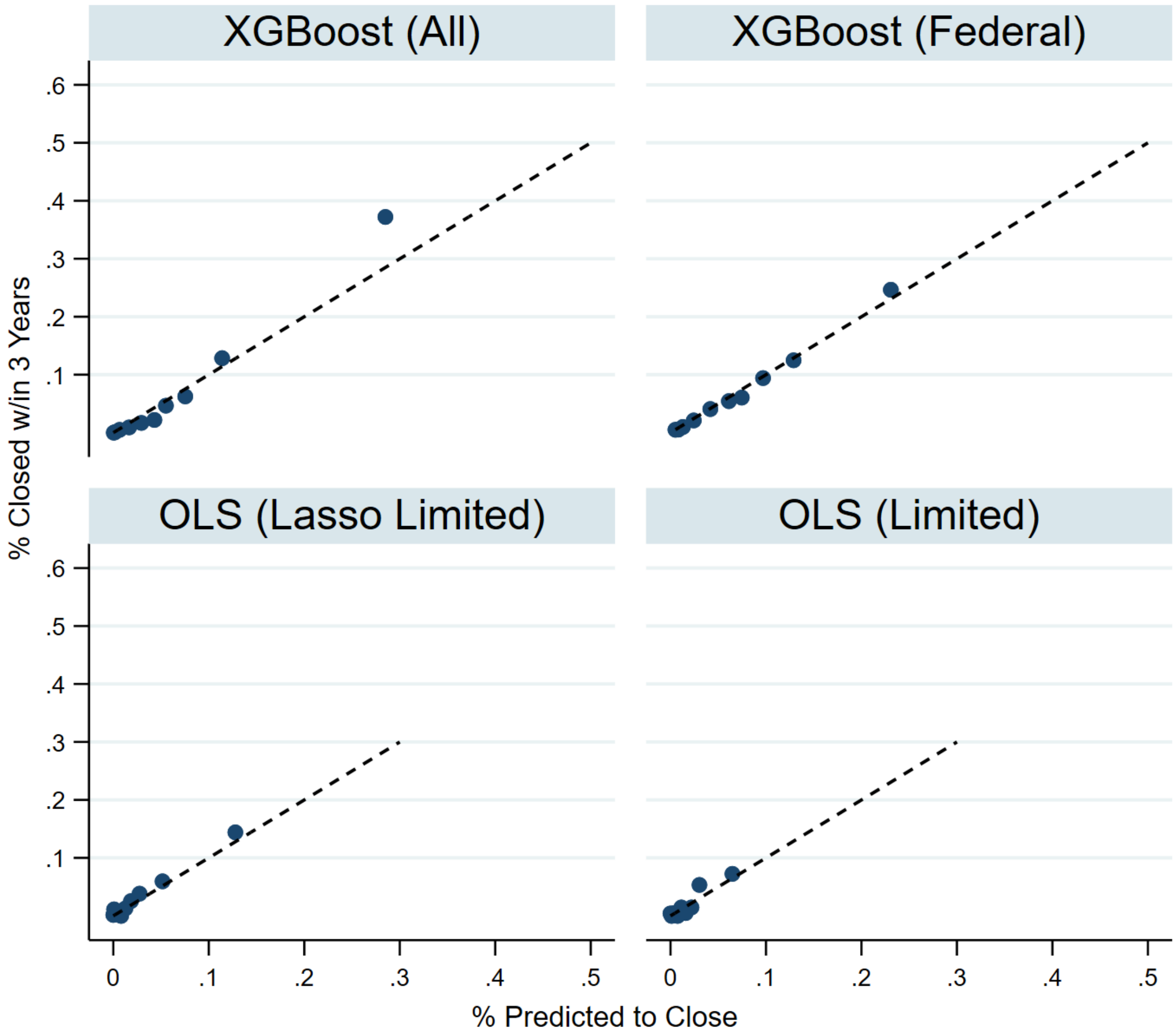
Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, and College Scorecard, 2001–2023

Figure 6a – Relationship between Predicted and Actual Closures, Share Institutions Closed by Prediction Decile, 2006–2021



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

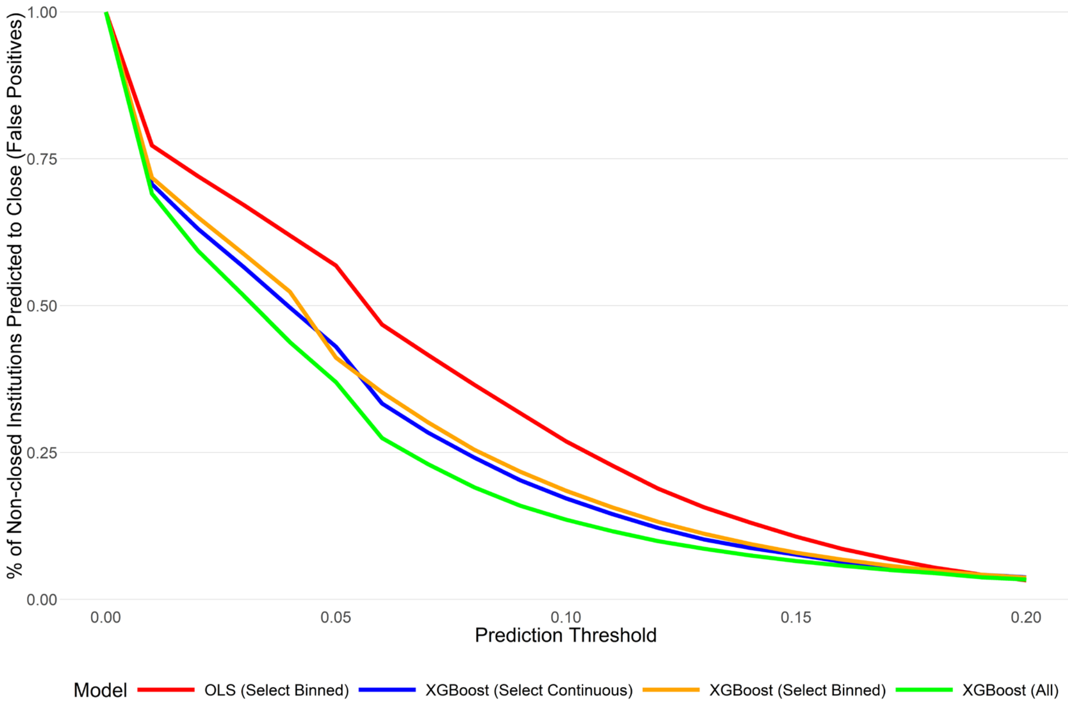
Figure 6b – Relationship between Predicted and Actual Closures, Actual v. Predicted Closures for Each Prediction Decile, 2006–2021



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

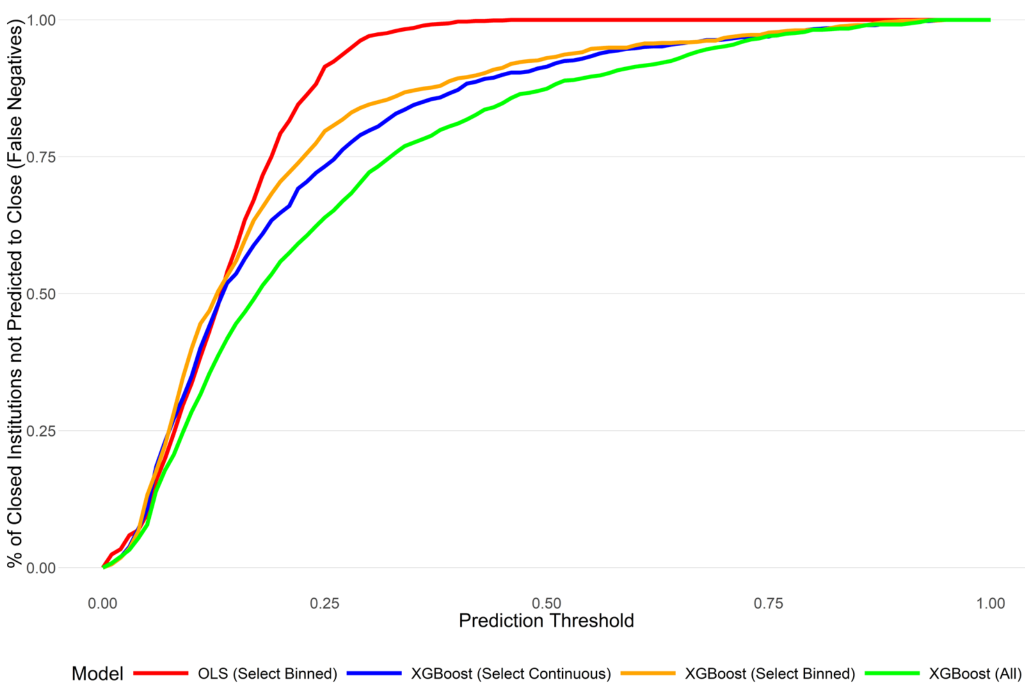
Notes: Dashed line represents the line where share of institutions predicted to close within three years would equal share actually closed within that time period.

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



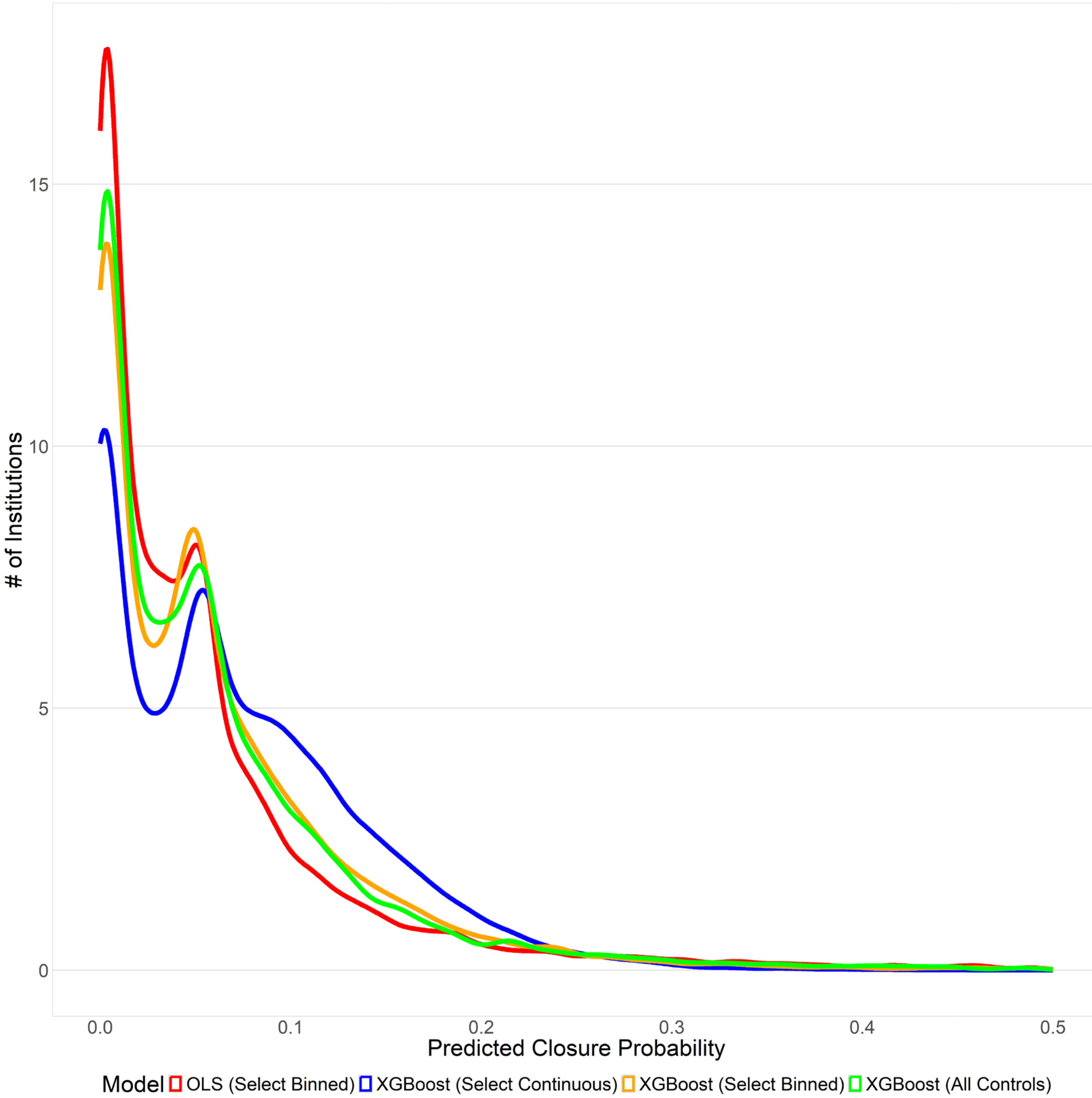
Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

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



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

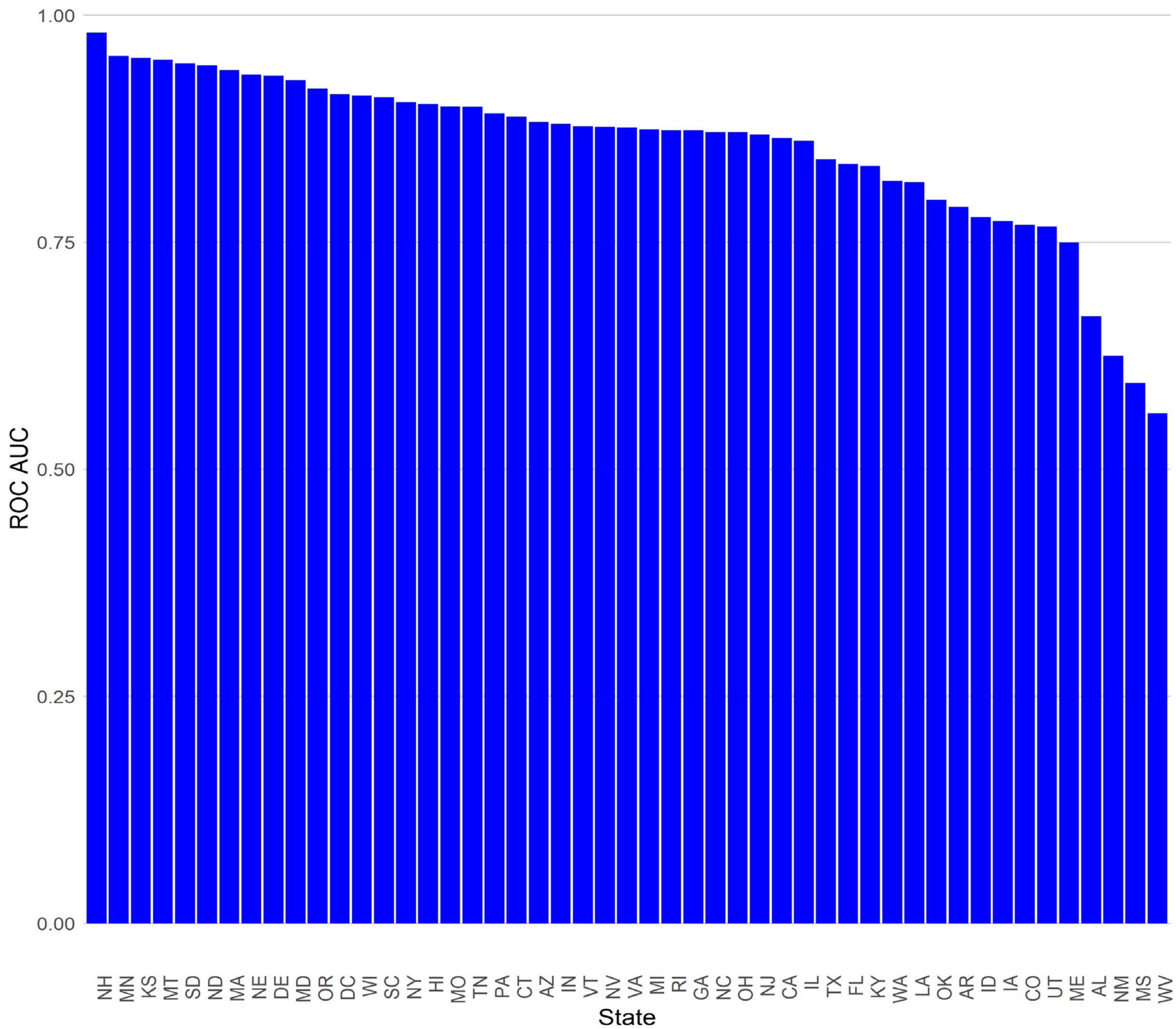
Figure 8 – Distribution of Predicted Closure Probabilities by Model, 2002–2023



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

Notes: Lines represent kernel density functions, concentrating on the portion of the distribution where the vast majority of the institutions' predicted closure probabilities (predicted closure probability of 0.5 or less) lie.

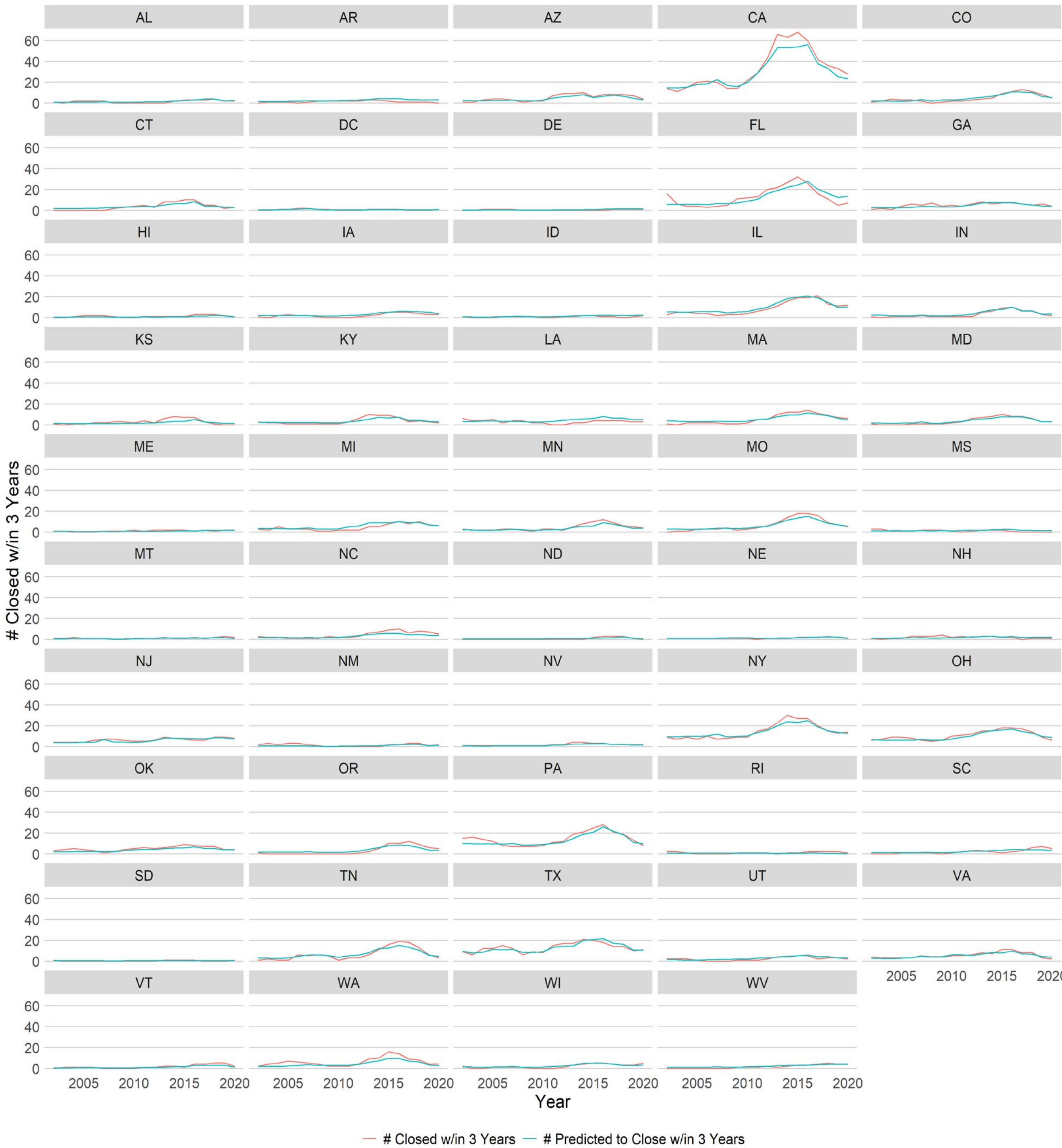
Figure 9 – Predictive Accuracy by State, Preferred Model, 2002–2021



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

Notes: Model is our preferred specification (XGBoost model with all controls) from Table 5. Model is trained on 75 percent of institution-year observations; predictions calculated for remaining 25 percent of observations. Closure is measured within three years of evaluation year.

Figure 10 – Actual v. Predicted Closures by State, Preferred Model, 2002–2021

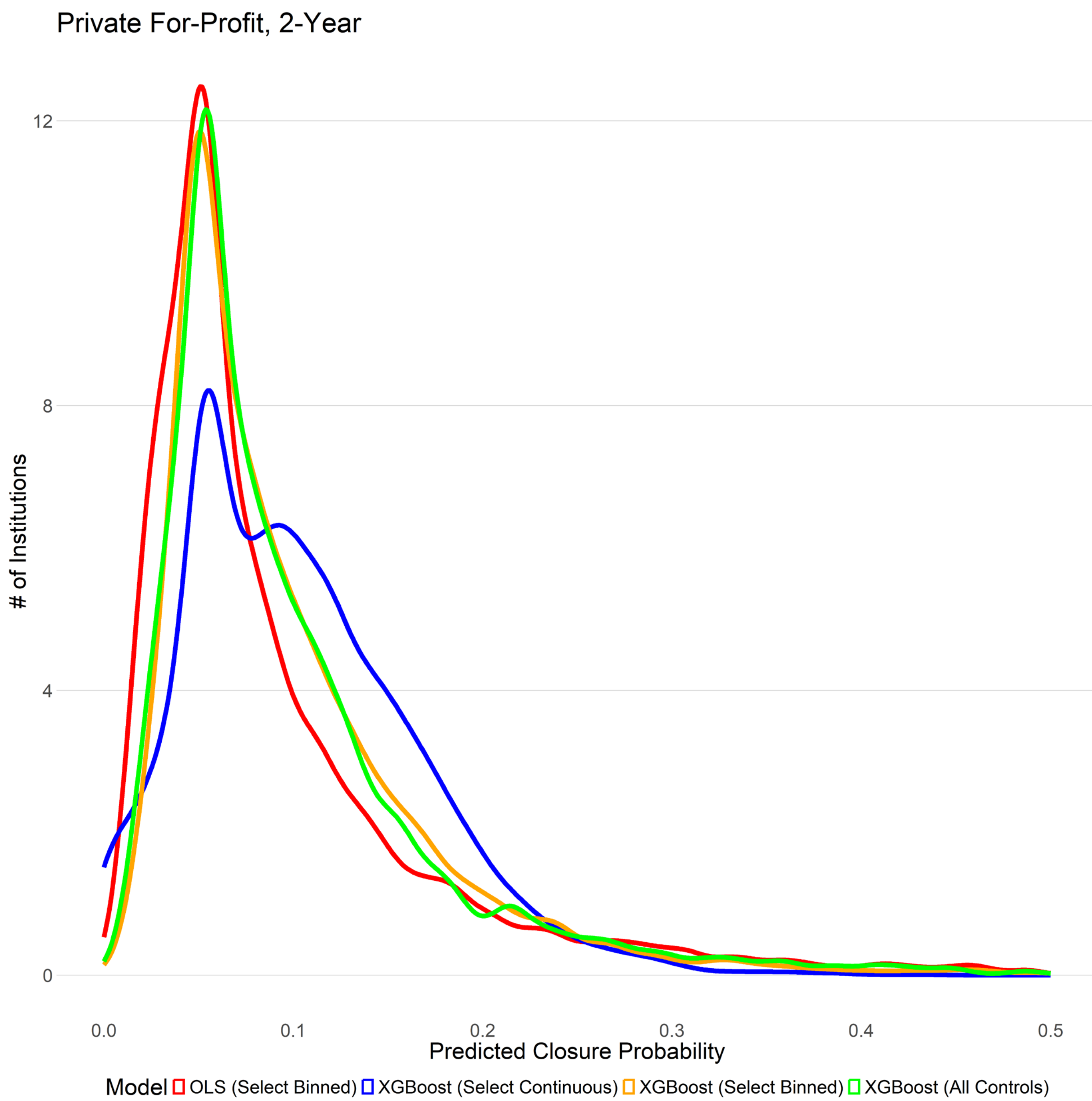


Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

Notes: Model is our preferred specification (XGBoost model with all controls) from Table 5. Model is trained on 75 percent of institution-year observations; predictions calculated for remaining 25 percent of observations. Closure is measured within three years of evaluation year.

Appendix A

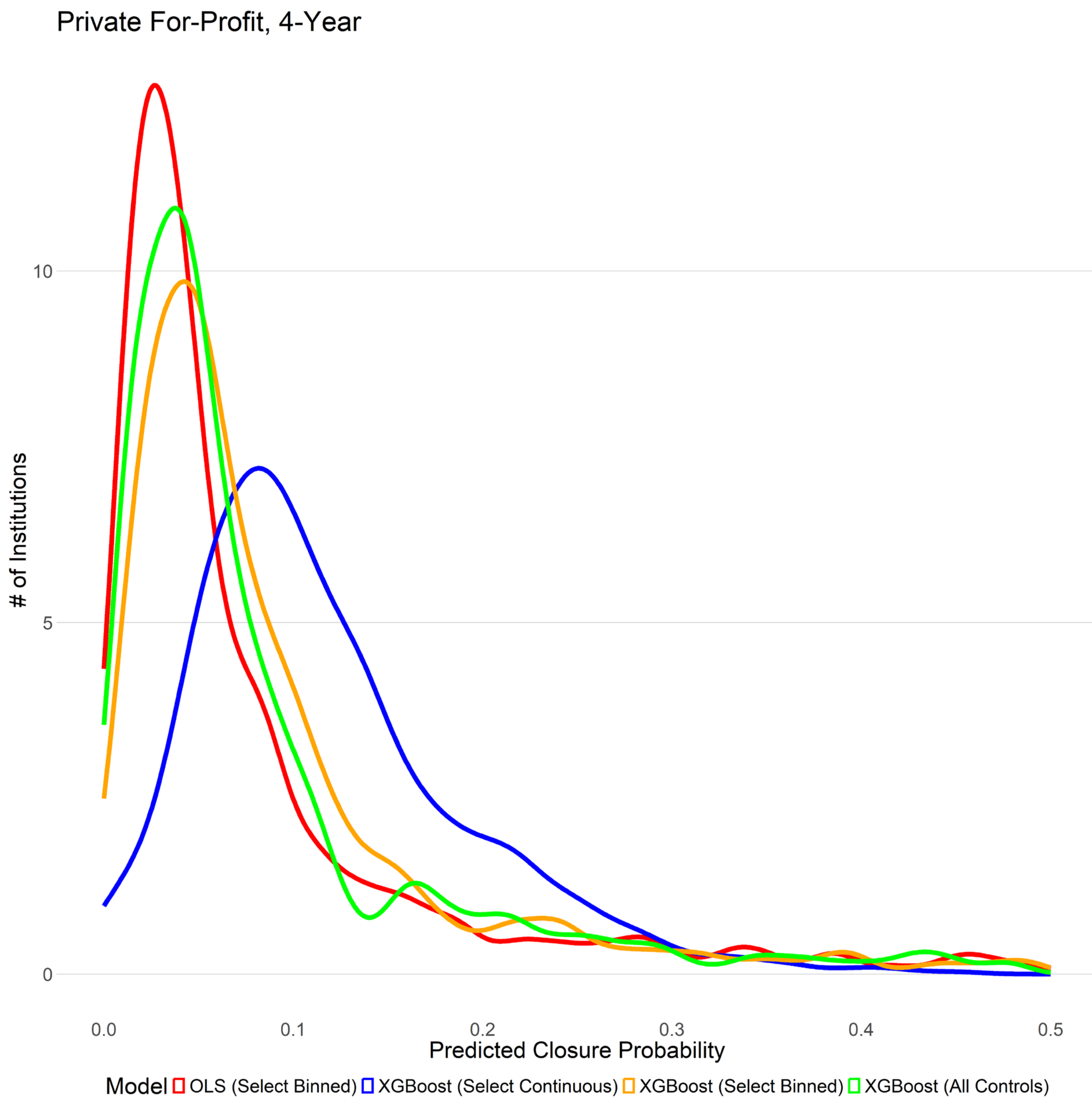
Figure A1a - Distributions of Closure Predictions by Model, Private For-Profit Two-Year, 2002-2023



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 1996–2023

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

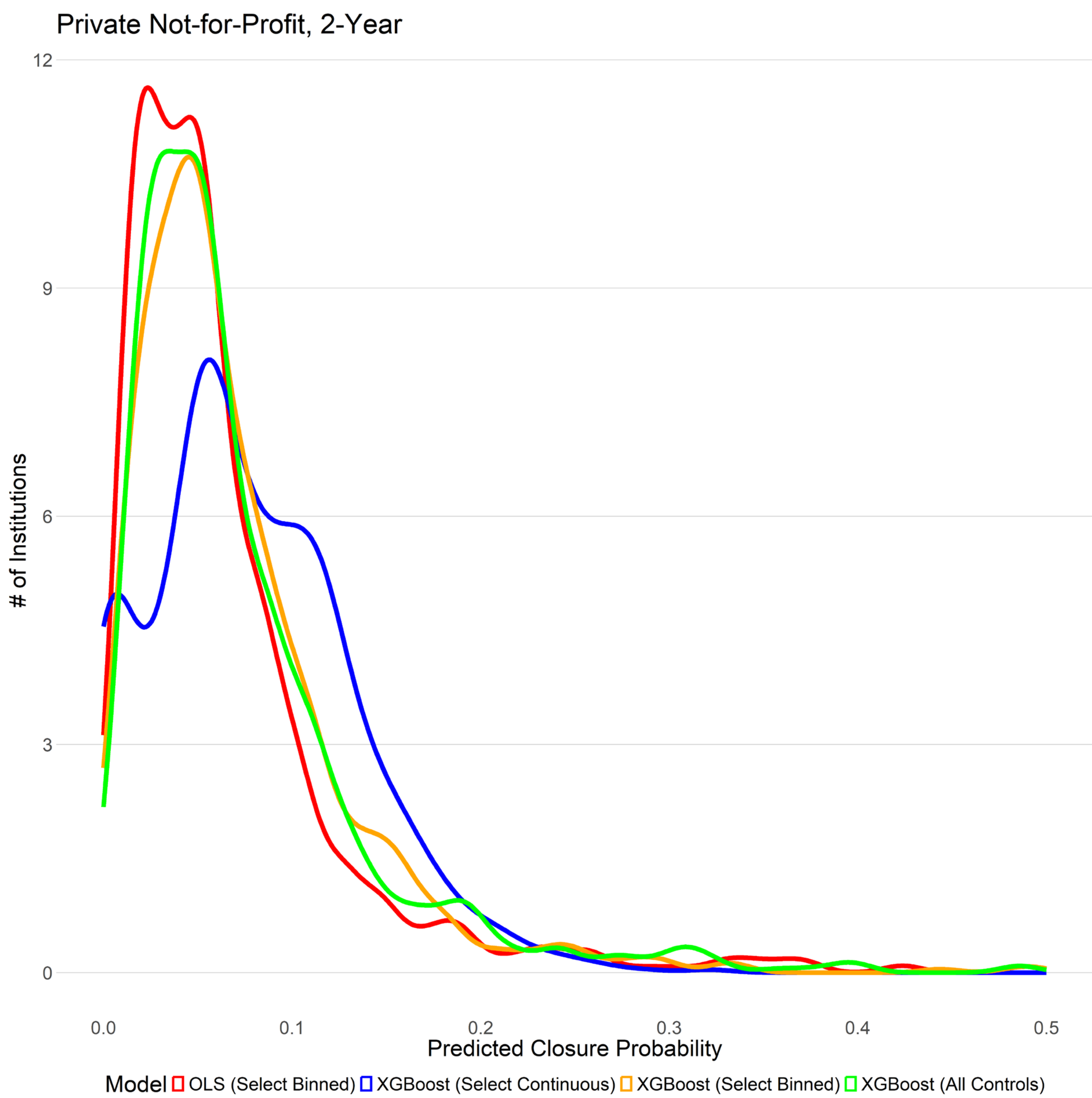
Figure A1b - Distributions of Closure Predictions by Model, Private For-Profit Four-Year, 2002–2023



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 1996–2023

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

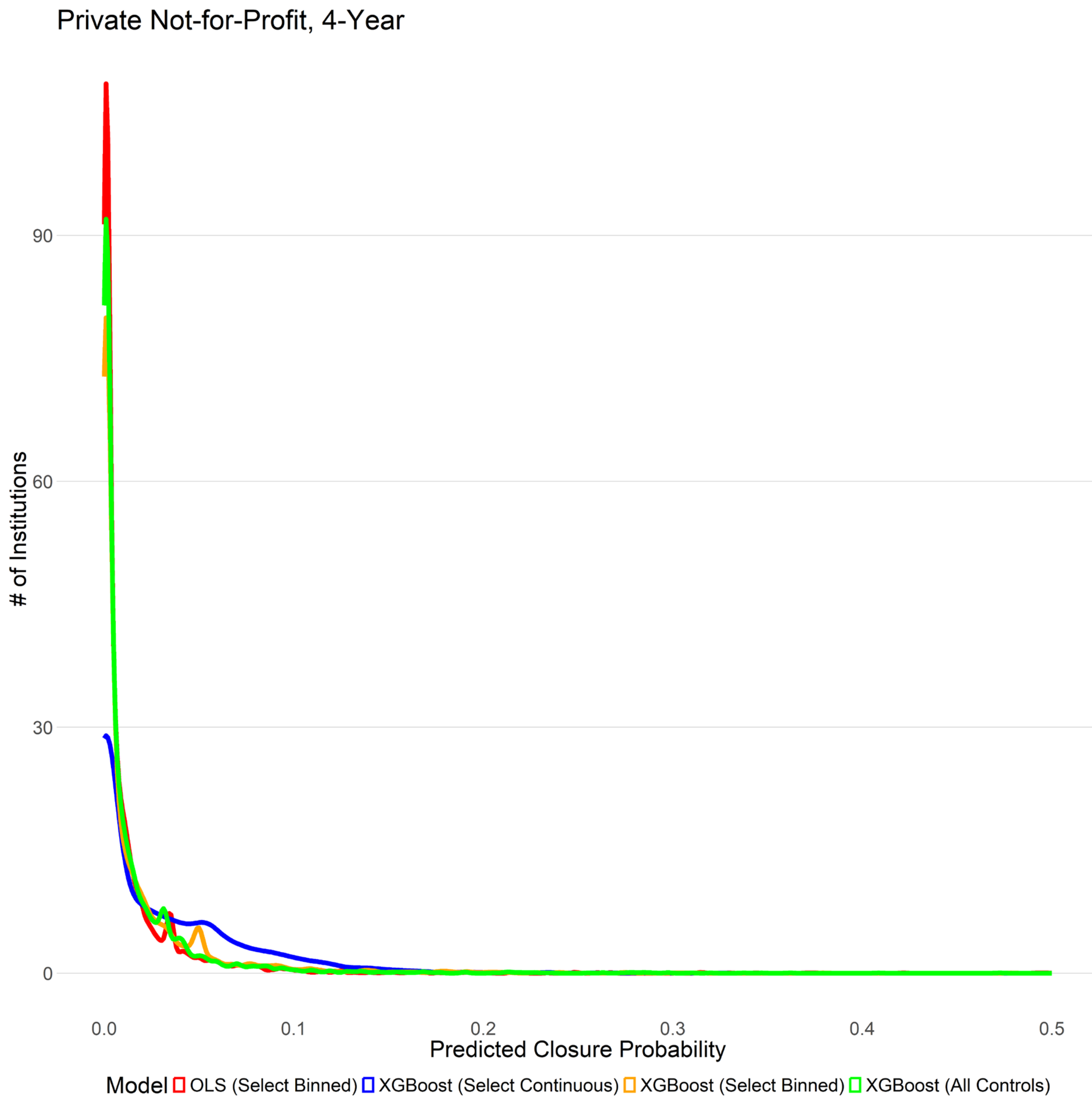
Figure A1c - Distributions of Closure Predictions by Model, Private Nonprofit Two-Year, 2002–2023



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 1996–2023

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

Figure A1d - Distributions of Closure Predictions by Model, Private Nonprofit Four-Year, 2002–2023



Source: Authors' calculations based on IPEDS, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 1996–2023

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

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, PEPS Closed School Reports, College Scorecard, Federal Student Aid, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and U.S. Bureau of Labor Statistics data, 2002–2023

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, two years before closure, because the data is predominantly missing in the year of actual closure.