Adaptation in the Accounting Labor Supply

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Abstract: The accounting profession has long attracted people seeking secure careers, but we hypothesize that fear of labor-replacing disruption has, in recent years, made accounting less attractive to students sensitive about economic security. Using exposure to contemporaneous mass layoffs in a student's hometown as a shock to the salience of economic security, we first show that layoff-exposed college freshmen were *more* likely to choose accounting during the 1990s but became *less* likely in the 2000s. This pattern is stronger when layoffs are attributable to technological disruption. The long-run perception of economic security in the accounting profession likely depends, in part, on the extent to which it adapts. To test this, we next measure the extent to which accounting curricula have adapted to technological change using course catalogs from a large sample of U.S. universities from 2009-2020. We show that accounting curricula have been slower to incorporate instruction about new technologies than other business disciplines and that attrition among accounting majors is significantly attenuated in accounting departments that increase technology-oriented coursework relatively quickly. Together, we show that 1) the accounting profession's place in the competition for high quality human capital is threatened by the perception that it is especially vulnerable to labor-replacing automation, but 2) this threat is sharply attenuated when accounting courses adapt to cover emerging technologies.

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I. INTRODUCTION

There is growing academic interest in the link between the labor for accountants and accounting outcomes (Barrios 2022, Hoopes et al. 2018), but there is scant research on the determinants of the labor supply for accounting over the long run (Carnes, Christensen, and Madsen 2023; Friedman et al. 2024; Le 2023). This is especially relevant as enrollments in undergraduate accounting programs have declined relative to other business majors since the mid-1990s, and in absolute terms since 2017, leading to a "pipeline crisis" that may have long-run consequences for the economic value of accounting-related services, the quality of information available to firm managers, financial reporting quality, trust in audited financial statements, and accounting education (AICPA 2023; Illinois CPA Society 2021; Maurer 2023b). Historically, accounting careers have been perceived as 'safe' because they have been perceived to be less sensitive to fluctuations of the business cycle (Leiby and Madsen 2017). However, in recent years, reports from federal agencies, academics, and the business press have popularized the claim that accounting work is particularly vulnerable to labor-replacing automation (BLS 2022; Dallas Morning News 2003; Maurer 2023a). "Accountants and Auditors" are ranked second in a list of occupations most likely to experience job losses due to computerization (Frey and Osborne 2013; The Economist 2014) and the Bureau of Labor Statistics (BLS) ranked "Tax Preparers" as one of the occupation groups most exposed to labor-replacing technologies (Handel 2022).

In this study, we examine how changes in the perceived skill requirements for professionals have disrupted the accounting labor pipeline. Has the apparent rise of labor-replacing automation threatened the perception that accounting careers are stable? Has the profession taken steps in response to "future proof" the discipline? Has traditional accounting education responded adequately to changes in the environment? In essence, we argue that today's students do not perceive the same level of *safety*, or even relevance, that was associated with their grandfather's, or even father's, view of a career in the accounting profession due to rapid technological developments over the past decades.

We first investigate whether the appeal of an accounting career to students has changed over time as a result of emerging labor-replacing technologies (e.g., computerization) that could reduce demand for accounting labor. Recent evidence suggests that the appeal of the accounting major to incoming college students is sensitive to their experiences in high school, including their exposure to financial reporting frauds committed by companies local to them (Carnes et al. 2023) and the exposure of local industries to "restrictive" accounting standards (Le 2023). We use variation in mass layoffs near a student's hometown in the year prior to starting college[1] ("local mass layoffs") as quasi-random shocks to their perceptions about future labor demand (Acton 2021) and preference for economic security.[2] Recent evidence from the labor and education economics literature suggest that when students and young workers—those most capable of adapting to evolving labor markets—witness mass layoffs, they likely migrate away from occupations they perceive as less secure, i.e., more susceptible to automation and less "future-proof" (Acton 2021; Feigenbaum and Gross 2024).

We expect exposure to local mass layoffs to increase the salience of economic security for prospective college students. However, we also expect that preferences for accounting careers have declined over our sample period 1995 to 2010 due to perceptions that technological developments

[1] We use the term "college" to mean education at the "post-secondary" or "tertiary" level.

[2] A prospective student's exposure to local mass layoffs likely increases the salience of economic security to them for two reasons. First, students are more likely to learn about labor demand shocks from mass layoffs occurring near where they live, and this is most likely to manifest as changes in preferences for economic security immediately prior to our measurement of career choices. Second, contemporaneous waves of automation and the China shock (Galle and Lorentzen 2024) caused local mass layoffs with substantial cross-sectional and temporal variation in the US. We tie this variation to students' hometown and timing of college enrollment, which allows us to isolate the preference for economic security from national business cycles and other long-term trends in higher education.

have made them less secure. Specifically, given the available evidence that accounting education attracted people who value economic security from the 1970s to the early 2000s (Leiby and Madsen 2017), we expect there is a positive association between exposure to mass layoffs and enrollments in accounting programs early in our sample period. However, we expect this pattern to reverse in the later years of our sample period as concerns increased that accounting is especially exposed to automation risk and that this reversal will be especially pronounced for students exposed to mass layoffs caused by automation.

Second, we examine efforts of the accounting profession to adapt to technological disruption and whether these efforts attenuate attrition from university-level accounting courses. Acemoglu and Restrepo (2018) study labor markets disrupted by automation and develop a conceptual framework that can explain why, despite contemporary predictions to the contrary, technological revolutions of the past have not led to persistent, widespread unemployment. Their basic insight is that technological innovation can automate some tasks that had previously been labor intensive, but it can also create new productive tasks that complement new technologies and are (at least with the technology of the time) not automatable. As recently noted by Andy Jassy (2025), the CEO of Amazon: "*We will need fewer people doing some of the jobs that are being done today, and more people doing other types of jobs*." As a result, it is possible to arrive at an equilibrium where technological progress does not cause mass unemployment. Critically, creating new tasks that complement emerging technologies requires investment in research (to develop the task) and in training (to prepare workers to perform the task).

The comparative advantage in the types of tasks performed by professions, or their "jurisdictions", shift as the economic environment changes and control of a given task by a given profession is determined by inter-professional competition (Abbot 1988). Adaptation to technological change likely plays an important role in this "race for relevance" (Illinois CPA Society 2021). Technological change disrupts labor markets but offers both opportunities and threats. The former, because technology augments some skills; the latter, because technology replaces some skills. The extent to which automation weakens demand for accounting labor is likely a function of the extent to which the accounting profession invests in the creation of new automation-complementing tasks, trains new entrants to the profession to perform these tasks, and does these things quickly and effectively enough that the accounting profession outcompetes adjacent professions to maintain control of these new and valuable work jurisdictions.[3] Thus far, evidence suggests that the net impact of technological change on the demand for accounting labor has been negative. Fedyk et al. (2022) find that audit firm AI investment is negatively associated with employment counts. In addition, Friedman, Sutherland, and Vetter (2024) show that industry-level investment in software from 2009-2019 is positively associated with the employment of people with business degrees but not necessarily people with accounting degrees. In this study, we connect the dots between changes in the nature of demand for accounting labor and the adaptation of the systems for developing accounting human capital to study how accounting has fared in the "race for relevance."

For our tests examining local mass layoffs and accounting enrollments, we use the Higher Education Research Institute's Freshman Surveys (HERI), a large dataset which includes the home zip codes of incoming college freshmen and their intended field of study. We also use the Mass Layoff Statistics of the Bureau of Labor Statistics (BLS), which uses unemployment claims (50 or more workers) to identify organizations that have experienced mass layoffs. The BLS contacts

[3] The hiring of new accounting graduates by CPA firms decreased by 10% in 2020 relative to 2019, while the recruitment of non-accounting graduates for accounting and finance roles increased by 10%. In 2020, 42.7% of new hires were from non-accounting backgrounds, an increase from 31% recorded in 2018 (AICPA, 2021).

these organizations to collect information about the reasons for the layoffs, including whether automation was the cause. We find that local layoff exposure is positively associated with the likelihood of majoring in accounting in the 1990s and negatively associated with the likelihood of majoring in accounting after 2000. Additionally, we find that students exposed to automation-related layoffs are significantly less likely to major in accounting than students exposed to layoffs due to other causes. We also find that mass layoff exposure is positively associated with concerns among college freshmen about paying for college and about post-graduation financial outcomes. These associations validate our proposed mechanism that layoff exposure increases the salience of economic security. Together, this evidence is consistent with our hypothesis that the perception that accounting careers are especially vulnerable to disruptive automation has made accounting education less appealing to students seeking stable careers.

For our tests examining efforts of the accounting profession and accounting educators to adapt to the challenges and opportunities presented by new technologies, we use a unique course catalog dataset from Light (2024) containing data on course titles, descriptions, and enrollment numbers from approximately 10 million courses across 105,741 department-years from a large sample of US colleges and universities over the period 2009-2020. We measure the extent to which coursework covers emerging technologies using counts of words and phrases associated with data analytics and technology in the course descriptions. These course catalogs show that, relative to 2009, the share of technology related accounting coursework has increased by a factor of 1.3, but this increase is far smaller than in other business disciplines, i.e., finance has increased by a factor of 2.5. We then examine attrition from accounting coursework by comparing the numbers of students enrolled in lower-level courses (i.e., 100- and 200- level), often required by multiple business school majors, to the numbers of students enrolled in upper-level courses (i.e., 300- and

400- level) two years later. We find that attrition from accounting coursework has been steadily increasing over our sample period (2009-2020), but it has decreased in non-accounting business disciplines. Finally, when we split the sample of accounting departments into those that increased coverage of technology and those that did not, we find no evidence of attrition in accounting departments that increased the extent of technology-related coursework but strong evidence of attrition in the accounting departments that did not.

We contribute to the growing literature on labor economics and accounting (Barrios 2022; Choi et al. 2024; Friedman, Sutherland, and Vetter 2024; Leiby and Madsen 2017; Madsen 2013; Madsen 2015). First, we show that, while the security of accounting careers was a critical component of the appeal of accounting education to students through the end of the 1990s, after 2000, accounting education became less appealing to security-oriented students because of the threat of labor-replacing technological innovation.

We also contribute to the literature on the accounting profession's adaptation to technological change. The accounting profession has taken steps to respond to the threat of automation. The AICPA added sections on information technology and business analytics to the 2024 CPA exam (AICPA 2024) and the PCAOB has issued new standards about the use of technology in the audits of public companies (PCAOB 2024). There are also indicators that audit firms are increasingly investing in artificial intelligence ("AI")[4] (Fedyk et al. 2022; Law and Shen 2020) and that technological change has created new markets,[5] or altered existing markets, for

[4] Some recent data suggest that accounting firms may state that they are adopting AI tools in their public communications but as few as 1 in 4 firms implemented AI tools by the beginning of 2024 (CFO.com 2024). We acknowledge that AI is a rapidly evolving technology and that the actual state of adoption may not be empirically observable for a few years. However, we argue that public communications on the implementation of AI tools may serve as a potential mechanism through which incoming students begin perceiving the accounting profession as particularly exposed to obsolescence.

[5] A few examples of evolving and brand-new subject matter audits "enabled" by new technology include internal control assessment (e.g., cryptosecurity), trust systems and access verification (e.g., TOIP, OI, GLEIF), crypto-related transactions, and block chain protocols and applications.

assurance services (e.g., smart contract audits) that could potentially be served by people with accounting-related education and training (Knechel, Maex, and Park 2023). But existing evidence suggests that the net impact of technological change on the demand for accounting labor has been negative (Fedyk et al 2022; Friedman, Sutherland, and Vetter 2024). We contribute to this literature by showing that accounting educators have added new technology-oriented coursework more slowly than those in other business disciplines. This result suggests that either the accounting profession has been relatively slow to develop new tasks that are augmented by emerging technologies or that, when the profession develops such tasks, accounting education has been slow to participate in exposing new students to the emerging technologies. These situations are consistent with relatively modest responses on the part of the accounting profession and accounting education to the threat of automation and offer an explanation for the finding that emerging technologies have had a relatively negative impact on the demand for accountants (Fedyk et al 2022; Friedman, Sutherland, and Vetter 2024).

II. CONCEPTUAL FRAMEWORK

2.1 Local Layoff Exposure and the Preference for Economic Security

Young people making decisions about college tend to rely on easily acquired information and often revise their preferences when presented with new information (Baker et al. 2018; Fricke et al. 2018). Prominent influences include socially proximate friends and family (Alvarado and Turley 2012; Goodman et al. 2015; Xia 2016), economic conditions (Ersoy 2019; Liu et al. 2018), and news events involving geographically proximate organizations (Carnes et al. 2024). Labor demand shocks can induce economic anxiety, cause a reassessment of “secure” career options. and shift expectations about the effect of future labor-replacing automation in specific professions

(Jeffrey and Matakos 2024). Consequently, we expect exposure to local mass layoffs to shift the preferences of students choosing their college majors upon entering a university.

While mass layoffs may occur due to the business cycle, trade, or idiosyncratic firm-level factors, those that are related to automation are particularly likely to induce shifts in long-term career preferences. Unlike other reasons for layoffs, automation represents a long-term shift in organizational business models and signals future trends in labor demand, particularly when automation is likely to be labor-replacing rather than labor-augmenting (Acemoglu, Kong, and Restrepo 2024). When students and young workers witness mass layoffs, they may avoid studying to enter occupations they perceive as more susceptible to automation and less "future-proof" (Feigenbaum and Gross 2024).[6] For example, community college students exposed to local mass layoffs switch away from programs that train skills most relevant to the occupation groups experiencing these layoffs (Acton 2021).

We expect mass layoffs that occur near a student's hometown will have an especially strong impact on student plans because of evidence that information travels efficiently within a local social network (Bell et. al 2019; Carnes, Christensen, and Madsen 2024), and because geographic constraints in labor markets mean local economic news is especially consequential. Local media is a likely information source, as they frequently report on mass layoffs and the reasons for them. Automation is a common theme in this coverage across place and time.[7] In addition, geographic "place-based" factors driven by ties to family and other mobility constraints

[6] When millions of female telephone exchange operators were laid off and replaced by mechanical switching technology between 1920 and 1940, future cohorts of female workers shifted to newer, higher productivity occupations, while incumbents moved to lower-paying jobs or remained unemployed (Feigenbaum and Gross (2024).
[7] Some examples include "Sears automation eliminates back-office jobs" (United Press International 1992); "More jobs lost to automation than foreign workers" (St. Louis Post Dispatch 1996); "High-tech lowers the boom on number of professions […] bookkeepers are among the occupations that have seen major cuts due to firms increasing their use of automation" (Dallas Morning News 2003); "Philips Lighting will lose 100 jobs to automation" (Knight-Ridder/Tribune Business News 2005); "Automation spurs Bally's to eliminate 200 jobs" (The Press of Atlantic City 2006).

play a large role in long run economic and health outcomes in the US (Finkelstein, Gentzkow and Williams 2021). Residents of areas that have experienced job losses do not readily relocate to areas with more job opportunities and may not do so even when presented with a large subsidy to relocate (CRS 2023; Bartik, 2020).[8] On average, geographic mobility in the US declined by more than 50% between 1980-2010 (Molloy, Smith, and Wozniak 2011).[9] Importantly, mass layoff events vary widely in location and time (see Figure C1 and C2), and hence are likely to have a quasi-random effect on student decisions. Using exposure to local mass layoffs as a shock to the preference for economic security enables us to focus on how variation in perceptions of local economic factors incrementally explains variation in choosing an accounting career (Blom, Cadena, and Keys 2021; Leiby and Madsen 2017).

2.2 Economic Security in the Accounting Profession

To formally model how preference for job stability impacts the expected value of lifetime career earnings, we use the framework for the investment value of a job-oriented education developed by Beffy et. al (2012), who model the investment value of a postsecondary education in a given major as the present value (discounted by *β*) of the sum of wage level (*w*) weighted by employment duration (*l*), both of which vary over time (*s*) by worker (*j*) and education level (*k*) as shown below:

$$\mathrm{V_{jk}} = \mathbf{E}\left(\overline{ln\, w_{jk}} \right) = \mathbf{E}\left\{ \left(\ln\left(\textstyle\sum_{\mathrm{s}=1}^{\mathrm{N}_s} \beta_{s,jk} (\mathrm{w_{s,jk}})(\mathrm{l_s}) \right) \right) \right\} \tag{1}$$

[8] Bartik (2020) estimates that a subsidy to induce relocation may need to be higher than the subsequent annual incomes of those in these distressed communities.

[9] Such "place-based" factors extend to larger social consequences. For example, localities with exposure to layoffs had a larger share of "deaths of despair" (suicide, drug overdose, and alcohol poisoning) and were concentrated in areas which previously had a higher share of manufacturing and mining operations in states like West Virginia, North Dakota, and South Dakota, referred to as "the forgotten America" in popular press (Graham 2021). Policymakers have embraced these findings. The US increased investments in "place-based" economic development programs such as the Build Back Better Regional Challenge. Europe has implemented European Union Structural Funds to promote economic development in distressed localities (Brookings 2023; Neumark and Simpson 2014).

Intuitively, the wage level (*w*) is only one component of the investment value of postsecondary education. The second component, duration of employment (*l*), implicitly reflects the preference for economic security. If an incoming student believes that the skills associated with an accounting education will become obsolete, their expectations of future employment duration in an occupation (*l)* will be lower, and therefore, *even when the wage level* (*w*) *does not change,* this student will value an accounting career less and will be less likely to major in accounting.

Layoff-exposed students, who are more sensitive to economic security, may be *more* likely to major in accounting if they perceive the profession as "a stable career" (Leiby and Madsen 2017), i.e., if E(*l*) is high, but may be *less* likely to major in accounting if they believe it is especially vulnerable to long-term disruptions in the viability of the career.[10] One possible channel, anxiety about technology replacing professional labor, has increased over the past few decades (Autor 2015). This may be particularly pronounced for accountants during the sample period of 1995-2010 since for example, the first widely popular version of Microsoft Excel debuted in the mid-1990s (Ginsberg 2024; Encyclopedia Brittanica 2024). If these cues have caused college freshmen to increasingly believe that a significant portion of the accounting profession is particularly exposed to technological disruption, we expect layoff exposure to increasingly discourage them from majoring in accounting. This leads to our first hypothesis:

> ***H1:*** *Exposure to local mass layoffs increases the salience of economic security and, therefore, has become increasingly negatively associated with the decision to major in accounting over time as the threat of labor-replacing disruption has developed.*

[10] Students may continue to believe accounting careers are stable despite technological disruption if they believe the accounting profession, particularly auditing, involves performing complex tasks requiring human judgment and a subjective interpretation of regulations. For example, auditing can be classified as a *credence* good, i.e., where neither the input needed nor the outcome is observable (Causholli and Knechel 2012, Darby, and Karni 1973, Dulleck and Kerschbamer 2006) and so certain types of work possible with an accounting education may be less exposed to automation. In other words, if incoming students who fear automation perceive accounting jobs as too complex to be readily automated, then they may select into the profession at a higher rate than others.

We are interested in the extent to which concern about long-term obsolescence has discouraged students from majoring in accounting, but a potential alternative explanation for declining accounting enrollments is that starting salaries for people with accounting training have declined relative to those with finance or other business training (AICPA 2023; Friedman, Sutherland, and Vetter 2024). Changes in relative starting salaries are unlikely to explain accounting enrollments during our sample period for two reasons. First, the relative enrolment decline experienced by accounting predates the relative decline in salaries by roughly *fifteen* years, which suggests that factors other than pay contribute to enrolment declines. For example, Friedman, Sutherland, and Vetter (2024) show that the relative share of accounting majors among business graduates in the American Community Survey (ACS) began to steadily decline in the mid-1990s. Data from the National Association of College and Employers' (NACE) annual starting salary survey displayed in Figure 1 show that relative starting salaries for graduates from accounting programs did not decline until after 2010, after which there is evidence of wage stagnation for accountants. Friedman et al. (2024) show that the mean and median pay received by ACS respondents of any age with an accounting bachelor's degree declined relative to the median pay received by respondents with finance degrees only in 2010 and beyond. Ellis and Overberg (2024) also show that trend in entry level pay for accountants was stagnant during the 2010s, while entry-level pay for financial analysts, marketing specialists, and management analysts substantially increased. Taken together, this evidence suggests that our results over our sample period of 1995-2010 are not due to wage stagnation in accounting.

Beyond this timing-based evidence, a second reason to expect that enrollment trends are not well explained by relative pay alone is that incoming college students have remarkably inaccurate information about starting salaries and employment rates across majors (Baker et al.

2018) and their knowledge about wages remains poor even by the time they are seniors (Betts 1996). Thus, while wages are an important input when students choose their college majors, the quality of their information about wages is likely limited by information acquisition and processing costs, which are likely especially impactful when relative wages have been changing recently and when changes in relative wages impact primarily non-entry-level workers with whom college students likely share few social connections. As noted earlier, the investment value of a postsecondary education (V_{jk}) is a function of expected pay and of expected employment duration over a career. Stagnating starting salaries may play a role in the attractiveness of the accounting profession in more recent years. Considering college students' limited information about relative wages combined with empirical evidence about enrolment trends for our sample period of 1995-2010, we argue that the longer-term secular decline of accounting enrollment as a share of undergraduate business students is likely associated with perceptions about the long-term relevance of accounting education in the age of information technology.

2.4 Adaptation in Accounting Coursework and Retention in Upper-Level Courses

Our first hypothesis relates to incoming first year students who likely have limited knowledge about the content of accounting curricula and the nature of accounting careers. Any relationship we find between layoff exposure and intention to major in accounting may, therefore, capture behavioral responses or "marketing problems" for accounting. Experience completing accounting coursework may change a student's perception about accounting as a career choice and the threat of automation. Consequently, we next examine students who have completed introductory accounting coursework, typically required for many business majors, and consider the ratio of these students that subsequently complete upper-level coursework (either majoring in accounting, minoring in accounting, or enrolling in accounting electives). In this way, we can distinguish between what may be considered “marketing problems” versus decisions that are more information-based. To relate this response to future economic security, we measure which programs are “adapting with the times” and study their retention of students in upper-level coursework. If accounting is adapting to technology as fast as other programs, then students who have been exposed to accounting coursework may be more likely to perceive accounting as “future-proof”.

Accounting departments may be relatively slow to develop new technology-oriented courses. There is evidence that accounting professionals have been especially reluctant to replace Microsoft Excel with other, more modern, tools (Buchheit et al. 2020; Schmidt et al. 2020). This reluctance to adopt new technology is consistent with evidence that accountants tend to resist reforms of many types. Madsen et al. (2022) show that accountants are especially likely to have a set of personal values called “conservation values” (Schwartz 1994) and provide evidence that, motivated by these values, accountants are skeptical of various social reforms. Among broad populations, conservation values are negatively associated with the uptake of new technologies (Blekesaune 2019). For example, audit firms resisted a requirement to provide assurance over XBRL data (Center for Audit Quality, 2009) when XBRL tagging of financial reports first went into effect, leading to an alternative assurance market led by technology firms (RDG Filings, 2024). If accounting professors share a similar reluctance to adopt new technologies as accounting practitioners and other people with conservation values, they will likely be relatively slow to develop new technology-oriented coursework. In addition, accounting departments may not innovate in the classroom as quickly as finance, marketing, or other business school departments because of CPA educational requirements. Most states in the US require students to enroll in specific upper-level accounting coursework. In turn, students may primarily demand courses that prepare them for the CPA exam, and this may make accounting curricula relatively rigid, leading to our next hypothesis:

H2*: Accounting coursework adapts to technology at a slower rate than other coursework.*

Requiring more hours of upper-level accounting courses directed at preparing for the CPA exam may make accounting curricula less adaptable and it may also make accounting education less attractive to students looking to double-major or pursue a technology minor. Students may perceive the opportunity costs of enrolling in an accounting program and pursuing a CPA license as particularly high because of the worry that the skills they acquire in college may not be "future-proof". This concern is likely magnified when the accounting curriculum is less adaptive to, or reflective of, developments in technology. Students who are exposed to accounting curricula at the lower level may continue in accounting if they perceive that coursework is adaptive to technological advances, and therefore more likely to be valuable in the future. If they are exposed to topics such as machine learning and data-driven decision-making in their accounting courses, they may be better prepared to perform tasks that complement new technologies and be less fearful about the likely effect of automation on their career in accounting. However, if students observe that these topics receive more attention in other disciplines, those who are concerned about automation may be less inclined to select upper-level accounting classes, leading to our final hypothesis:

H3*: Retention in upper-level accounting coursework is positively associated with its adaptation to technology.*

III. DATA, RESEARCH DESIGN, AND SAMPLE SELECTION

3.1 Local Layoff Exposure and Quantity of Incoming Students

We first investigate how the exposure of incoming first-year students to hometown layoffs is associated with their intention to major in accounting. We define our variables in Appendix A, and discuss the construction of key variables in Appendix B.

Validating ML_Exposure

In our primary tests, we model selection of accounting as a major as a function of exposure to local mass layoffs (*ML_Exposure*). We expect layoff exposure will increase the salience of economic security. We test this expectation by examining the association of layoff exposure with students' answers to two questions in the HERI survey, one measuring whether the student is concerned about their ability to afford college (*Cost Sensitive*) and the other measuring whether the student is concerned about post-graduation financial outcomes (*Wage Sensitive*). For these tests, we estimate the following linear probability model:[11]

$$\textit{Cost Sensitive (or Wage Sensitive)} = \beta_0 + \beta_1 \textit{ML\_Exposure} + \beta_c \textit{Controls} + \gamma_y + v_f + \epsilon \qquad (2)$$

We include university (v_f) and year (γ_y) fixed effects in Equation (2) to control for time-invariant and period-specific factors, respectively, probability weight the observations according to survey weights, and cluster standard errors by university. We follow Carnes, Christensen, and Madsen (2023) and control for self-reported demographic factors like sex (*Female*), race (*Minority*), whether the student is a first-generation college student (*Firstgen*), parental income decile (*Income*), and whether students' parents are accountants (*Paccounting*). Additionally, we control for academic aptitude, including high school grade point average (*HSGPA*) and relative performance on standardized tests (*SAT_ACT*); and broader economic trends, including economic

[11] Following Carnes, Christensen, and Madsen (2023), we use probability-weighted and survey-weighted linear probability models because they are more tractable than alternative estimation methods given our sample size, HERI's complex survey design, and the large number of fixed effects in our models. Employing linear probability models for dichotomous outcome variables is supported by Angrist and Pischke (2009) and common in recent research (e.g., Carnes, Christensen, and Madsen (2023); Christensen (2016); Hanlon and Hoopes (2014)).

growth in recent years in the student's home state (*GDPgl4*)[12] and the unemployment rate in the state in year *t* (*Unemploy*). See Appendix A for more details. If *ML_Exposure* causes quasi-random variation in anxiety about students' economic futures, then it should be associated with *Cost Sensitive* and *Wage Sensitive*, even when holding socio-economic status and broader economic trends constant, validating that *ML_Exposure* is a reasonable shock to a student's preference for economic security. We perform robustness tests in Appendix C for alternative measures of layoff exposure, including a continuous measure and an extreme values measure to provide evidence that our results are not sensitive to this variable definition.

Layoff Exposure and the Likelihood of Majoring in Accounting

Next, we estimate models explaining variation in *Accounting,* which is an indicator variable that equals 1 when a student's intended major is accounting, similar to the dependent variable in Carnes, Christensen, and Madsen (2023). These models implement our tests of H1, that exposure to local mass layoffs increases the salience of economic security and, therefore, has become increasingly negatively associated with the decision to major in accounting over time as the threat of job-replacing technological disruption has developed. We first estimate the association between *Accounting* and *ML_Exposure* using the following linear probability model:

$$Accounting = \beta_0 + \beta_1 \, ML\_Exposure + \beta_c \, Controls + \gamma_y + \nu_f + \epsilon \qquad (3)$$

The specification is identical to Equation (2) except that the dependent variable in Equation (3) is *Accounting*. A significant coefficient on *ML_Exposure* would suggest that the likelihood of majoring in accounting is associated with exposure to local mass layoffs over our sample period.

Our hypothesis relates to changes in this relationship over time. To estimate how the relationship between *ML_Exposure* and *Accounting* changes over time*,* we recompute Equation

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[12] We control for broader state-level economic trends in order to be conservative with our set of controls and allow for *ML_Exposure* to capture variation in exposure to economic uncertainty over and above broader regional trends.

(3) for the sample before 2001 and the sample after 2001, which splits the sample in half (approximately). Additionally, we re-estimate Equation (3) by interacting an indicator variable for each year with *ML_Exposure* as detailed below:

$$Accounting = \beta_0 + \beta_1\, ML\_Exposure{*}Year + \beta_c\, Controls + \gamma_y + \nu_f + \epsilon \quad (4)$$

Consistent with H1, we expect the coefficient on *ML_Exposure* to decrease significantly over time.[13]

To provide additional evidence on the mechanism through which *ML_Exposure* affects the decision to major in accounting, we employ an instrumental variables approach to instrument for *Cost (or Wage Sensitive)* using *ML_Exposure* and tabulate the results in Appendix C as a robustness test. Students may report being sensitive about future income or ability to pay for college for a myriad of reasons, potentially biasing a straightforward OLS estimate. Our argument is that layoff exposure induces a preference for economic security among students (and induces quasirandom variation in their answer to questions about economic security), and that in turn changes major preferences. Eq (2) tests for the relevance criteria directly. Layoff exposure is unlikely to change a student's preference of major conditional on attending college through other mechanisms, implying that *ML_Exposure* likely addresses the exclusion criteria.

3.2 Adaptation in Accounting Coursework and Retention in Upper-Level Coursework

The models described in the prior section focus on the planned field of major of incoming college freshmen from 1995-2010 and our estimations of them will, therefore, be informative about the beliefs of students about accounting before they have had significant personal exposure to accounting courses. We next examine how the appeal of coursework changes with exposure to accounting. Specifically, we examine how enrollment in entry-level accounting courses is

[13] In both analyses, our year-by-year findings are consistent when splitting by the sample using a baseline year of 2000 or 2002.

associated with subsequent enrollment in upper-level accounting courses. US colleges and universities publish course catalogs and schedules online, which often include course titles, number of students enrolled, and a brief text description of the course content, usually in a machine-readable PDF format. Light (2024) compiles this information into a unique "course catalog" dataset which contains data from approximately 10 million course-level observations and 105,741 department-year level observations from a sample of US colleges and universities covering a large sample of undergraduate accounting students from 2009-2020.[14]

In Figure 3, we plot the total undergraduate enrollment in the US in upper-level coursework across accounting, finance, and information systems departments from 2009-2020. Figure 3 shows that while accounting enrollment grew from approximately 80,000 students in 2009 to approximately 100,000 students in 2017, finance grew from approximately 80,000 to 150,000 and information systems grew from 20,000 to 40,000 in the same period.

Modeling Adaptation to Technological Advances

We identify technology-related courses using "regular expression" based textual searches of course descriptions to identify those containing the words technologies, technology, software, and tech.[15] College students may learn about course content from academic advisors, college websites, professors, or fellow students and may not directly rely on course descriptions listed on a university's online catalog. However, the text of the course description is likely to capture variation across courses within a department that incorporate emerging technologies, and changes

[14] The raw data from Light (2024) contains data from 1998-2020, but data from 1998-2007 covers significantly fewer institutions due to missing historic course catalog data. In Figure 3, we plot the total enrollment in upper-level coursework in accounting from the course catalog data. The total in 2020 was 91,236, which is 20% higher than the unique number of first-time CPA test takers in 2021 (72,271). For more detailed validation of this data against public IPEDS data, please refer to Appendix A of Light (2024).

[15] We use the regular expression "\b(technologies|software|technology|tech(?!niques))\b", which identifies courses that mention variations of phrases related to "technology" or "software" while omitting mentions of the word related to "techniques," which happen to frequently appear in long-existing accounting curriculum.

in the number of courses related to emerging technologies are likely to capture department-level initiatives to adapt to changes in the demand for technology-related skills.

In Table 1, we list the titles of courses we most frequently flag as technology related, broken out by business school department. Across finance, marketing and business administration, flagged courses have titles like "fintech," "cryptocurrencies," "digital marketing," "business data analysis," "social media marketing" and "technology entrepreneurship." These titles were added to course catalogs during our sample period of 2009-2020, suggesting they were new or updated courses. The most frequently flagged course titles in our sample are accounting courses, concentrated in courses titled "accounting information systems", or sometimes feature in coursework focused on auditing, managerial, tax or financial accounting, which have been offered throughout the sample period. This is explained, in part, by greater standardization of accounting course titles. It also reflects the descriptive result that, at the beginning of our sample period in 2009, accounting offered a comparatively high concentration of technology-related courses, suggesting that, prior to our sample period, accounting had been a leader among business school disciplines in adaptation to earlier waves of technological disruption.

During our sample period, accounting introduced relatively few new technology-related courses. Figure 5 Panel A shows that 3.4% of accounting courses mention technology-related phrases in their course descriptions in 2009, which was higher than finance (1.4%) or marketing (3.2%) but lagged behind in introducing new courses through the sample period. By 2020, 4.5% of accounting courses mentioned technology-related phrases, but the share of tech-related finance courses increased to 3.7% and the share of tech-related marketing courses increased to 6.8%. Figure 5 Panel B shows the rate of change in tech-share more directly, and shows that accounting was the slowest among business school departments to adapt to emerging technologies.[16] Some examples of newer technology-related accounting courses that appear frequently in the dataset include “information systems auditing,” “comp audit and it controls” and related coursework in information security and information technology audits.

Using data from course catalogs, we investigate whether accounting departments adopt new technology in their curriculum at a rate commensurate with other business school departments during our sample period to test H2, that accounting coursework adapts to technology at a slower rate than other coursework. To examine this relationship, we estimate the following linear probability model on our sample of department-year observations:

$$Adapt\_Tech = \beta_0 + \beta_1 Accounting\_D + \beta_c Controls + \gamma_y + v_f + \epsilon \quad (5)$$

We include university (v_f) and year (γ_y) fixed effects in Equation (5) to control for time-invariant and period-specific factors, respectively, and cluster standard errors by university. *Adapt_Tech* is an indicator variable equal to 1 for a department if the portion of upper-level coursework containing technology-related phrases and words (listed in Table 1) increased from the previous year.[17] *Accounting_D* is an indicator variable equal to 1 for accounting departments and zero otherwise. Our controls include indicator variables equal to one for comparison groups of disciplines, including *Business* for non-accounting business departments, and *Tech* for Computer Science and Engineering departments. Additionally, we include *Log Enroll* as a control variable which is defined as the natural logarithm of enrollment at the university. The inclusion of *Log*

[16] A possible limitation of our measure of technology related coursework is that it understates the extent of adaptation within coursework that does not reflect changes in course descriptions: e.g., the use of “Alteryx” within an upper-level audit class. However, these types of changes are not prominent and therefore less likely to be advertised by departments to attract enrollment, compared to new coursework or concentrations that may reflect department-wide initiatives to attract students looking to train in emerging technologies demanded by the labor market. We believe our measure of technology related coursework captures the latter and we argue that this is most likely to capture department-wide initiatives aimed at adapting to changes in labor demand.

[17] We consider changes in the content of upper-level coursework as they are more likely to reflect changes in major requirements and less likely to reflect perfunctory changes in introduction classes.

Enroll should control for any association between university-level enrollment changes and tech-related coursework. All variable definitions are in Appendix A. Consistent with H2, a negative coefficient for *Accounting_D* would suggest that accounting departments are less likely to increase technology-related coursework than other disciplines.

Modeling Retention in Upper-Level Coursework

Next, we estimate the relationship between *Pct_Retention* and *Accounting_D* to test H3, that retention in upper-level accounting coursework is positively associated with its adaptation to technology. We estimate this relationship with the following OLS model:

$$Pct\_Retention = \beta_0 + \beta_1 Accounting\_D + \beta_c Controls + \gamma_y + v_f + \epsilon \qquad (6)$$

Other than the dependent variable, this specification is identical to Equation (5) with the same control variables, fixed effects, and clustering. A significantly negative coefficient on *Accounting_D* would suggest that accounting departments retain a lower percentage of students in upper-level coursework when compared to other departments. Next, we re-estimate Equation (6) after dividing the sample of accounting department-years into those that add new technology-related courses (*Adapt_Tech* = 1) and those that do not (*Adapt_Tech* = 0). We include observations from non-accounting departments in each estimation sample and compare the coefficient on *Accounting_D* for accounting department-years that increased and did not increase tech-related course offerings. Consistent with H3, a significant negative difference in coefficients between these two subgroups would suggest that accounting departments that adapt to emerging technologies are better able to retain students in upper-level coursework.

3.4 Sample and Descriptive Statistics

Sample Selection

We use HERI's freshman survey, BLS' Mass Layoff Statistics, and hand-collected course catalog data for our analyses. We use student-level characteristics, educational preferences, concerns about economic outcomes, test scores, parental details, socio-economic background and home zip codes from the HERI freshman survey. We use BLS data for the number of mass layoff events, number of workers affected, and reasons for layoffs, which we tie to students' home zip codes and time of graduation from high school. For our analyses of college freshmen choosing their college majors, we restrict our sample to 1995-2010 due to the availability of both HERI and BLS data. This sample contains 5,134,043 student observations. After removing observations with missing data for a student's home zip code, intended college majors, and observations with missing values from the BLS/BEA county data, our test sample includes 2,268,877 student-level observations. The course catalog dataset (Light 2024) includes 10 million individual observations of courses offered from 2009 to 2020 from a sample of 147 US colleges and universities that offer 4-year degrees. It includes enrollment counts in lower-level and upper-level courses from 120,637 university-department-year observations. The total enrollment in upper-level accounting coursework in 2020 in our sample was 91,236. For comparison, the number of accounting bachelor's degrees awarded in 2020 was 51,031 (AICPA 2023) and the number of unique CPA test takers in 2021 was 72,271 (AICPA 2023). Together with the validation tests in Light (2024), the evidence suggests that our course catalog data contains information from a large representative sample of undergraduate accounting students in the US. We have 105,741 university-department-year observations with required data for our H2 tests. We detail the sample selection procedure in Table 2.

Descriptive Statistics

In Panel A of Table 3, we present summary statistics for the HERI sample. The mean value of *Accounting* is 0.024, indicating that 2.4% of students in the sample intended to major in accounting, 59.6% of students in the sample are *Wage Sensitive* in that they answered that post-graduate salaries were "very important" as a factor in their decision to attend college, and 11.8% of students in the sample were *Cost Sensitive* in that they were "very worried" about their ability to pay for college. On average, 1.2% of the local labor force lose their job in a "mass layoff" in county-years in our sample. The mean value of *ML_Exposure* is 0.505, meaning that 50.5% of the students in the sample were "exposed" to local mass layoffs to a degree that was above the state-level median in a given state and year. The mean values of the demographic variables indicate that 54.5% of the sample are female students, 9.4% identify as a member of a minority racial/ethnic group, 16.1% identify as first-generation college students, and 6.6% of students have at least one parent who was an accountant. The mean value of *Income* is 5.67, indicating that the average student is between the 5th and 6th decile of parental income. In terms of academic aptitude, the mean value of *HSGPA* is 6.479, indicating that the average grade in high school is between a B+ and an A- and the mean value of *SAT_ACT* is 0.532, meaning that the average student's standardized test score is in the 53rd percentile.[18] The mean value of *AutomationRelated* is 0.081, indicating that 8.1% of students are from state-years with at least one automation-related layoff event. The mean value of *PostCPA150* is 0.471, indicating that 47.1% of the sample are from state-years where the 150-hour rule has been implemented.

In Panel B of Table 3, we present summary statistics for the course catalog sample. The mean value of *Pct_Retention* is 0.112, meaning that on average, enrollment in higher-level classes

[18] *Income* and *SAT_ACT* were defined for the whole HERI sample prior to sample restrictions, and hence we see slight deviations from the expected mean values of 5.5 for *Income* and 0.5 for *SAT_ACT*. These values align with Carnes, Christensen, and Madsen (2023).

within a department is 11% higher than enrollment in lower-level classes.[19] The mean value of *Adapt_Tech* is 0.297, indicating that 29.7% of departments increase technology-related coursework from the prior year. The mean value of *Accounting_D* is 0.011, indicating that 1.1% of the department-years in our sample are from accounting departments. The mean value of *Business* is 0.044, indicating that 4.4% of the department-years in our sample are from business school departments other than accounting. Together, this means that 5.5% of department-years are from business schools, and that accounting makes up about 20% of the observations from business schools. The mean value of *Tech* is 0.082, indicating that 8.2% of department-years are in computer science and engineering departments. The mean value of *Log Enroll* is 11.142, indicating that the sum of enrollment in all courses in a university is 69,009 on average.[20]

IV. MAIN RESULTS

4.1 Local Layoff Exposure and Quantity of Incoming Students

Table 4 presents the results from estimating Eq. (2), which models the likelihood that students are *Wage Sensitive* and *Cost Sensitive* as a function of *ML_Exposure*. We model the likelihood of students being *Wage Sensitive* in column (1) and (2), and *Cost Sensitive* in column (3) and (4).

In Columns (1) and (2), the coefficients on *ML_Exposure* are positive and significant. This result indicates that layoff-exposed students are more likely to be worried about post-graduation salaries. In terms of economic significance, the column 2 coefficient on *ML_Exposure* (0.010, p <

[19] Department-level differences in the extent of lower-level and upper-level coursework offered might explain why departments have a higher level of enrollment in upper-level courses and some departments have a higher-level of enrollment in lower-level courses. For instance, most business departments have one or two 100-200 level courses and substantially more 300-400 level courses.

[20] *Log Enroll* proxies for enrollment at the university, and changes in *Log Enroll* within a university over time are be correlated with changes in college-level enrollment, but this number should not be interpreted as the number of unique students attending a university, since students are typically registered for multiple courses in a given year. Assuming the average student is registered for 5 courses in a year, this would imply that the average university-level enrollment is roughly 69,009/5 = 13,801.

0.001) signifies that students with above median exposure to mass layoffs are 1 percentage point more likely to be wage sensitive. Compared to the base-rate probability of being *Wage Sensitive* (0.596), this represents an increase of about 1.7%. The coefficients on *ML_Exposure* are also positive and significant in Columns (3) and (4), which indicates that layoff exposed students are more likely to be worried about paying for college. In terms of economic significance, the coefficient on *ML_Exposure* (0.027, $p < 0.001$) in Column 4 signifies that students with above median exposure to mass layoffs are 2.7 percentage points more likely to be cost sensitive. Compared to the base-rate probability of being *Cost Sensitive* (0.118), this represents an increase of about 22.9%. These results validate the idea that *ML_Exposure* induces economic anxiety in students, a result that is stronger for anxiety about paying for college than for anxiety about post-graduate salaries (0.0174, $p < 0.01$). These results also support that *ML_Exposure* proxies for economic anxiety incremental to a student's demographic factors, socioeconomic status, academic aptitude, and broader economic trends, and provides validation to the idea that local layoff exposure is a quasi-random shock to the students' preferences for economic security.[21]

Table 5 presents the results from estimating Eq. (3) for the likelihood of students majoring in accounting as a function of *ML_Exposure.* In Column (1) and (2), the coefficients on *ML_Exposure* are both positive (0.003 and 0.003, $p < 0.01$) and indicate that, relative to the base rate probability of majoring in accounting (0.024), above median exposure to mass layoffs is associated with an increase in the likelihood of majoring in accounting of 12.5%. In Columns (3) and (4), we split the sample to before 2001 and after 2001 and re-estimate Eq. (3). In Column (3), the coefficient on *ML_Exposure* is positive (0.011, $p < 0.01$) and signifies that above median exposure to mass layoffs is associated with an increase of 40% in the likelihood of majoring in

[21] These results also provide evidence of the relevance criteria for the instrument variables analysis in Appendix C.

accounting relative to the base rate in the years prior to 2001 (0.027). In contrast, in Column (4), the coefficient on *ML_Exposure* is negative (-0.008, $p < 0.01$) and signifies that above median exposure to mass layoffs is associated with a 33% *lower* probability of majoring in accounting relative to the base rate after 2001 (0.023). These results are consistent with H1.

Our results suggest that local mass layoff exposure is positively associated with the likelihood of majoring in accounting in the first half of our sample period but negatively associated with the likelihood of majoring in accounting in the second half of our sample period. In Figure 2, we plot the year-by-year version of Eq. (3) to document the pattern we find in Table 5. The reversal of the sign of the coefficient occurs gradually over time and is the most negative in the most recent years in the sample. Figure 2 therefore suggests that our main results are unlikely to be driven by fluctuations in the business cycle. In Panel B of Figure 2, we compare the association between *ML_Exposure* and the likelihood of majoring in accounting, finance or technology-related majors. We find that as the association turns negative for accounting, it becomes more positive for finance and technology majors. This result suggests that layoff exposed students on average are less likely to major in accounting in the more recent years in our sample, and more likely to major in finance or technology-related majors. This finding is important because it suggests that the shift in the preferences of security-driven students away from accounting began long before the absolute number of students majoring in accounting began to fall in 2017.[22]

Automation-Related Layoffs

To focus our tests more sharply on automation, we re-estimate Eq. (3) after splitting our measure of layoff exposure into two measures: one for automation-related layoffs and one for non-automation-related layoffs. Columns 1 and 2 of Table 6 focus on the first half of our sample period

[22] We find consistent results in our instrument variables analysis in Appendix C.

(the years prior to and including 2001), and Columns 3 and 4 of Table 6 focus on the second half of our sample period (the years after 2001). Table 6 column (1) shows that, for automation-related layoffs, the coefficient on *ML_Exposure* is insignificant, while column (2) shows that, for non-automation-related layoffs, the coefficient on *ML_Exposure* is positive and significant (0.011, $p < 0.01$). The difference between these coefficients is negative and significant (-0.013, $p < 0.01$). These results suggest that local mass layoff exposure in the first half of our sample period was positively associated with the likelihood of majoring in accounting only for non-automation-related layoffs, i.e., we do not find evidence that security-driven students exposed to automation-related-layoffs were more likely to major in accounting in the first half of our sample period.

Table 6 column (3) shows that for the second half of the sample period, the coefficient on *ML_Exposure* for automation-related layoffs is negative and significant (-0.022, $p < 0.01$), while column (4) shows that the coefficient on *ML_Exposure* for non-automation-related layoffs is also negative and significant but by a smaller magnitude (-0.008, $p < 0.01$). The difference between these coefficients continues to be negative and significant (-0.014, $p < 0.01$). These results suggest that automation-related layoffs are more *negatively* associated with the decision to major in accounting than non-automation-related layoffs. In terms of economic significance, the difference between the coefficients on *ML_Exposure* in Table 6 across these two types of layoff exposure signifies that the probability a layoff-exposed student will major in accounting is 1.4 percentage points lower when layoffs are automation related than when they are not after 2001. Compared to the base-rate probability of majoring in accounting after 2001 (0.023), this amounts to a -61% difference.

4.2 Adaptation to Technological Advances and Retention in Upper-Level Coursework

Table 7 presents the results from estimating Eq. (5), which models *Adapt_Tech,* an indicator variable equal to one for university-department-years that had a year-over-year increase in the share of technology related upper-level courses. In Column (1), the coefficient on *Accounting_D* is negative and significant (-0.046, $p < 0.05$) which signifies that accounting departments are less likely to increase the share of technology-related coursework than other departments. In terms of economic significance, this coefficient signifies that accounting departments are 4.6 percentage points less likely than an average department to increase the share of coursework that is technology related. Compared to the base probability that a department adds technology-related coursework of 0.297, this represents a difference of -15.5%. This is consistent with H2, that accounting departments are slower to adapt to technology than other departments.

In contrast, the coefficient on *Tech* is positive and significant (0.073, $p < 0.01$) and signifies that computer science and engineering departments are 24.6% more likely to increase the share of coursework that is technology-related than an average department in the sample in a given year. The coefficient on *Log Enroll* is negative and significant (-0.150, $p < 0.01$) and implies that a doubling of university-level enrollment reduces the probability of increasing the share of technology-related coursework by 10.4%.[23] This result signifies that larger universities are slower to adapt coursework to cover emerging technology. While the coefficient on *Business* is positive but not significant (0.031, $p < 0.13$), column (2) shows that the difference between the coefficients on *Accounting_D* and *Business* is negative and significant (-0.077, $p < 0.01$). Column (3) shows that the difference between the coefficients on *Accounting_D* and *Tech* is also negative and significant (-0.119, F stat. = 26.54). Together, these differences indicate that accounting departments are 7.7% less likely to increase the share of technology-related coursework than are

[23] This value is the coefficient (-0.15) multiplied by ln(2), where 2 signifies doubled enrollment.

other business school departments in a given year, and 11.9% less likely to increase the share of technology-related coursework than computer science and engineering departments.

Figure 4 and Table 8 show results from our analyses of *Pct_Retention*, which is the percentage difference between upper-level enrollment in a department in year *t* and lower-level enrollment in the same department in year *t-2*. Panel A of Figure 4 plots the median value of *Pct_Retention* for accounting departments and all other departments over our 2009 to 2020 sample period as a percentage of their 2009 values. It shows relatively steady retention levels across non-accounting departments, but that accounting retention was relatively steady from 2009 to 2013 and then declined steadily through 2020. Table 8 presents the results from estimating Eq. (6), which models *Pct_Retention* as a function of *Accounting_D*. In Columns (1) and (2), the coefficients on *Accounting_D* are negative and significant (-0.178/-0.120, $p < 0.01/0.05$). This signifies that retention of students from lower-level courses to upper-level courses is lower in accounting departments than in other departments.[24] Across all departments in a university, enrollment in upper-level courses is on average 11% higher than in lower-level courses two years prior (Table 3). The column 2 coefficient on *Accounting_D* of -0.12 is economically large and signifies that enrollment in upper-level accounting courses is about 12% lower than in an average department, meaning that it remains virtually the same as enrollment in lower-level courses two years prior (the sample mean of 0.11 less the coefficient of -0.12% = -0.01).[25] In Columns (3) and (4), we split

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[24] A possible explanation for these effects could be that we are observing structural differences between accounting and other departments, and that retention in accounting departments is always lower. To estimate the change of retention in accounting departments over the years, we re-estimate Eq. (6) but with *Accounting_D* interacted with indicator variables for each year holding 2010 as the baseline. Panel B of Figure 4 presents the results from this specification and shows that relative to 2010, retention in accounting departments declined steadily through 2020, confirming the descriptive trend from Panel A.

[25] In untabulated analyses, we re-estimate Eq (6) with a discretized version of *Pct_Retention* splitting department years into negative retention (*Pct_Retention* < 0) and positive retention (*Pct_Retention* > 0) groups and find that accounting departments are 17% more likely to have a drop in upper-level enrollment compared to lower-level enrollment when compared to the sample mean.

the accounting departments into those that increase the share of technology-related coursework and those that do not, and find that retention for accounting departments that increase the coverage of technology in their curricula is about the same as average retention (0.002, $p < 0.183$) but far lower for accounting departments that do not increase coverage of technology (-0.231, $p < 0.000$; the difference between these coefficients is 0.229, $p = 0.015$). Overall, these results are consistent with H3, that retention of students in upper-level coursework is positively associated with adaptation to technology.

This result suggests that students who have been exposed to accounting coursework in business schools are less likely to major, minor or choose to take accounting electives in departments that dare slow to adapt to technological advances. Combined with our results from Table 4 and Table 5, these results are consistent with the idea that students are motivated to build human capital that is more likely to retain its value in the future and be more in demand in the contemporaneous market for professional labor, i.e., students favor college coursework that is adaptive to market, economic, and technological change.

Our analyses, taken as a whole, are consistent with a compelling trend in accounting education. Our primary results suggest that economically anxious students who were once especially attracted to accounting education no longer were attracted to accounting after 2001 because of the upswing in concerns about automation, i.e., after 2001 they became *less* likely to major in accounting. This result has important implications for the future of accounting education in the current highly uncertain economic environment. Assumptions about accounting enrollments that have held in the past (e.g., that students are especially attracted to accounting during recessions) may be less likely to be true in today's market. However, our evidence suggests that accounting departments can protect themselves against these general trends by better adapting curricula to technological change. Specifically, we find that enrollment attrition from accounting coursework among college students who have been exposed to lower-level accounting classes is concentrated at universities where accounting coursework is slow to adapt to emerging technologies. Accounting departments that have been more adaptive have experienced more robust enrollments.

V. SUPPLEMENTAL TESTS

As a regulated profession, a student's decision to go into accounting, and the degrees of freedom that a university has in designing their accounting curriculum, may be sensitive to the requirements for obtaining a CPA license which may limit the flexibility of accounting programs to adjust to trends in technology. In this section, we investigate whether the stringency of state-level CPA licensing standards is associated with the addition of technology-related courses by accounting departments and with retention of students in upper-level accounting coursework.

Curriculum Adaptation and Restrictive CPA Course Requirements

State CPA boards generally specify how many hours of upper-level accounting coursework are required to meet the educational requirements for a CPA license. Even after the passage of the 150-hour rule in a state, the extent of upper-division accounting coursework required for an accounting degree varies significantly across states, ranging from 12 hours (Arizona) to 54 (Utah), with a median value of 24 credit hours. The more hours that are required in an accounting degree program, the fewer hours are available for other classes. We now analyze the restrictiveness of the accounting curriculum in a state, defining *Restrictive* as an indicator variable that equals 1 for state-years with more than the median (24) number of required upper-level accounting credit hours after the passage of the 150-hour rule.

These results are reported in Table 9 for *Adapt_Tech* with the sample split on *Restrictive*. The coefficient on *Accounting_D* is negative and significant for the entire sample (-0.046, $p < 0.05$), as was previously observed in Table 7. It is also negative and significant for states with high levels of required accounting coursework (-0.054, $p < 0.05$). However, it is not significant in states which allow more flexibility in designing the coursework for an accounting degree (-0.037, ns). The difference between the Column (2) and (3) coefficients is not significantly different from zero, however. This result suggests that the rate at which accounting departments adapt their curricula to cover novel technology does not differ across states with above and below median licensing restrictiveness.

In Table 10, we present the results from estimating Eq. (6), which models retention of students in upper-level courses (*Pct_Retention*) with the sample split by *Restrictive*. The coefficient on *Accounting_D* is negative and significant for the entire sample (-0.120, $p < 0.05$), as was previously observed in Table 8. It is also negative and significant for states with high levels of required accounting coursework (-0.243, $p < 0.05$). In Column (3), the coefficient on *Accounting_D* is positive but not significant (0.026, ns). The difference between the coefficients in Column (2) and (3) is negative and significant ($p < 0.01$). These results suggest that the retention of students in upper-level accounting coursework is significantly lower in states that require a larger number of accounting credits for CPA licensure.

Overall Table 10 suggests that students who take low level accounting coursework are less likely to continue on to upper-level coursework in states that require above median accounting credits to qualify for a CPA license, i.e., restrictive licensing requirements may contribute to the declining attractiveness of an accounting major. The result also documents a new unintended cost of the 150-hour rule in addition to others demonstrated in the literature recently (Barrios 2022, Dai et al. 2024, Sutherland et al. 2024), if the extra hours are not devoted to timely and valuable learning experiences.

VI. CONCLUSIONS

In this study, we examine how changes in the perceived skill requirements for professional job seekers have disrupted the accounting labor pipeline. Specifically, we examine two research questions. First, we investigate whether incoming college students are less likely to major in accounting when exposed to mass layoffs, especially due to automation, near their homes immediately before starting college. Second, we investigate whether college students who have taken accounting coursework are less likely to continue to enroll in upper-level coursework when the content of accounting education is less adaptive to emerging technologies.

We offer three main results. First, we use data describing millions of college freshmen and data on layoffs to show that local layoff exposure is positively associated with the likelihood of majoring in accounting in the 1990s and negatively associated with the likelihood of majoring in accounting in the 2000s. This result is driven by layoffs that are attributable to automation and not to layoffs attributable to other factors. Second, we find that, from 2009-2020, accounting departments lagged other departments in adapting curricula to cover emerging technologies. Third, we find that accounting departments that increase coverage of emerging technologies retain more students who took lower-level accounting courses in upper-level courses when compared to other accounting departments. Collectively, these results suggest that the perception that accounting careers are stable and “future-proof” weakened steadily through the 1990s and 2000s and, as a result, accounting education became steadily less appealing to economically anxious students. As the wave of technological change continued through the last decade, accounting curricula increased coverage of new technologies more slowly than the curricula of other departments and this relatively slow adaptation contributed to the declining attractiveness of the accounting degree.

Technological change generates economic threats to, and opportunities for, the accounting profession (Acemoglu and Restrepo 2019). Historically, when new technologies with the potential to expand economic productivity have emerged, it has taken years or decades for organizations to build complementary institutions that enable them to effectively exploit these opportunities (Brynjolfsson et al. 2021). The accounting profession, including its regulators (PCAOB 2024), firms employing accountants (CFO.com 2024; Fedyk et al. 2022; Law and Shen 2020), and accounting educators (Ballantine et al. 2024), is now engaged in the challenge of responding to increasingly rapid technological change. Our study offers a window into the process of attracting and preparing entrants into the profession given the ongoing disruption and lagging adaptation of the profession. We show that the perception that accounting is vulnerable to technological disruption calls into question one of the profession's historical selling points, its security. We further show that efforts by accounting departments to adapt to technological disruption by introducing new technology-oriented material into their curricula can reduce this problem, but that, since 2009, many accounting departments have been relatively slow to adapt. If relatively limited training in the uses of novel technologies in accounting has limited the extent to which these technologies augment, rather than replace, accounting labor, it could explain why people with accounting training have fared relatively poorly in industries and professions making large investments in technology (Friedman et al. 2024). There are opportunities for the accounting profession to expand into new work tasks that are more likely to be augmented than replaced by technology, including information assurance and smart contract assurance (Knechel, Maex and Park 2024). Educating students to better prepare them to perform such tasks may be a means of making accounting education more attractive and valuable to economically anxious students and potential employers.

As with any archival study, we acknowledge a few limitations. First, we acknowledge that our findings likely serve as one of several long-term causal explanations for changes in the attractiveness of the accounting profession, including changes in occupational licensing standards and the regulatory landscape, e.g., SOX. Second, despite the novelty and extent of our student-level and course-level data, we cannot speak to the potentially unobservable decision-making process both behind students' choice of majors and institutions' choice to create and change course offerings. These questions may be best suited for future research conducted through qualitative or experimental methods. Third, we acknowledge that we have limited ability to comment on the advent of generative artificial intelligence (AI) and its effects on the perception of economic security in the accounting profession. We argue that our study provides context to how students concerned about economic security have selected away from the profession in the era of rapid computerization, but less is known about if these results apply to the era of generative artificial intelligence, particularly as initial labor market trends in entry-level software occupations suggest a concentrated loss of economic security in technology-related majors relative to accounting. As the technology landscape rapidly evolves and more data becomes available, future research can extend our study to more recent years to study the effect of the advent of generative AI on the attractiveness of the accounting profession and adaptation in higher education.

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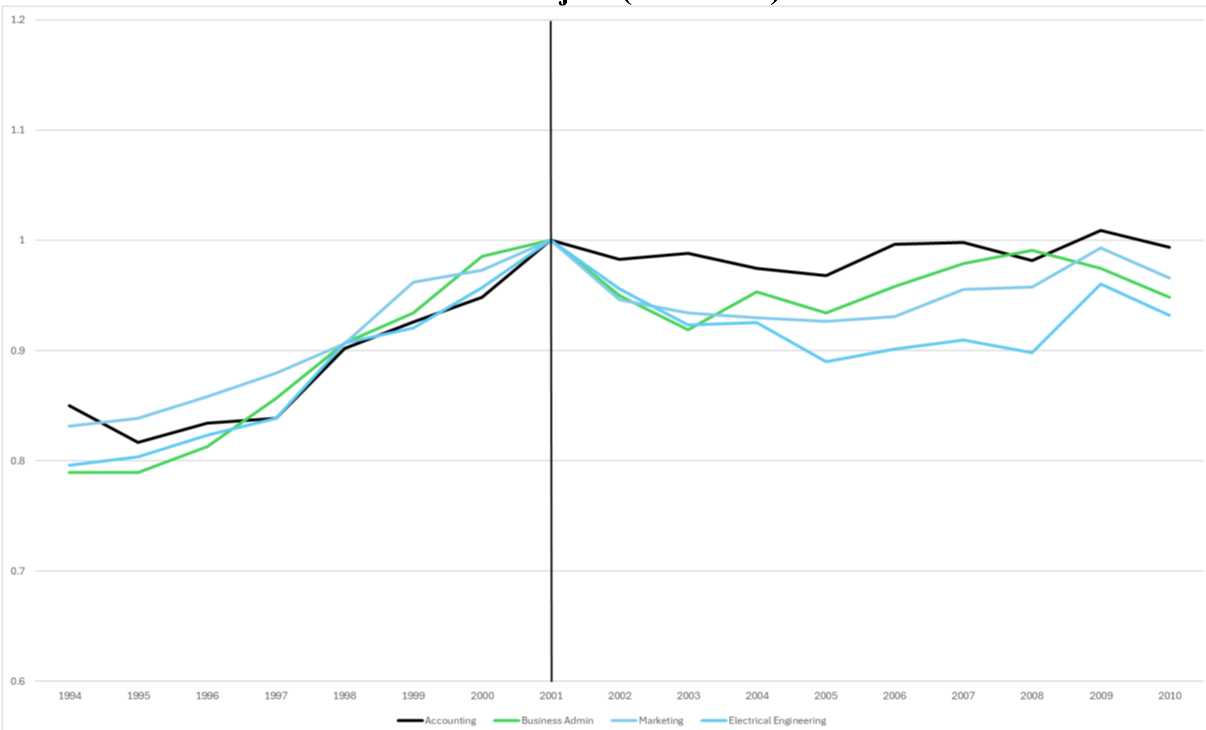
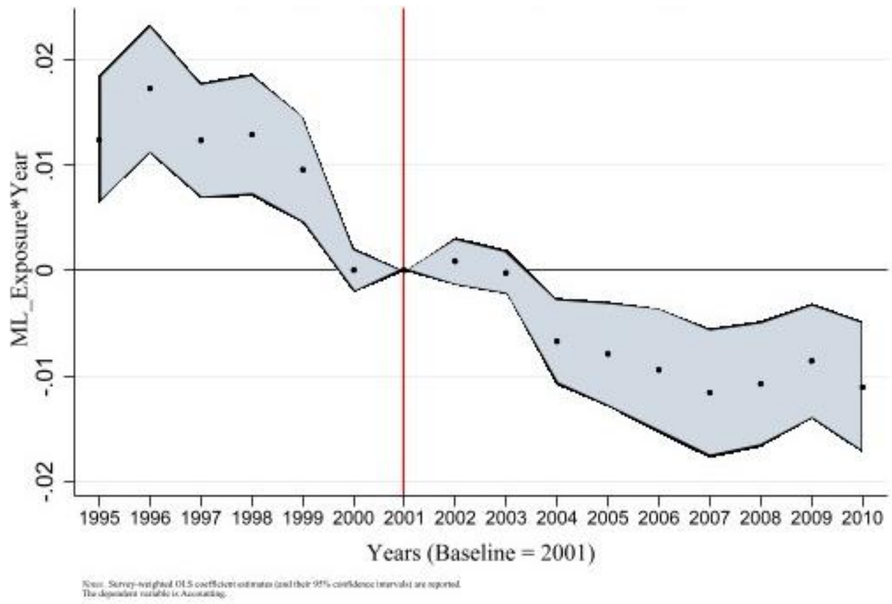
Figure 1: Inflation-Adjusted Starting Salaries for Accounting Majors vs. Other Business Majors (1994-2010)



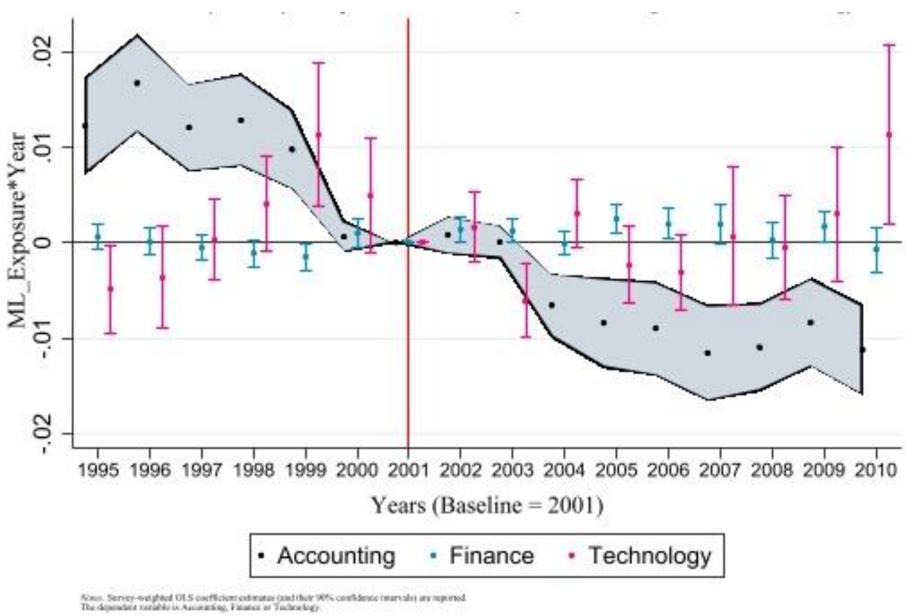
This figure presents the inflation-adjusted starting salaries earned by graduates from Accounting programs (Black), Business Administration, Marketing, and Electrical Engineering relative to 2001. The data for this chart is from the National Association of College and Employers' (NACE) annual starting salary survey.

Figure 2: Panel A – The Relationship between Layoff Exposure and Incoming Accounting Majors by Year (1995-2010)



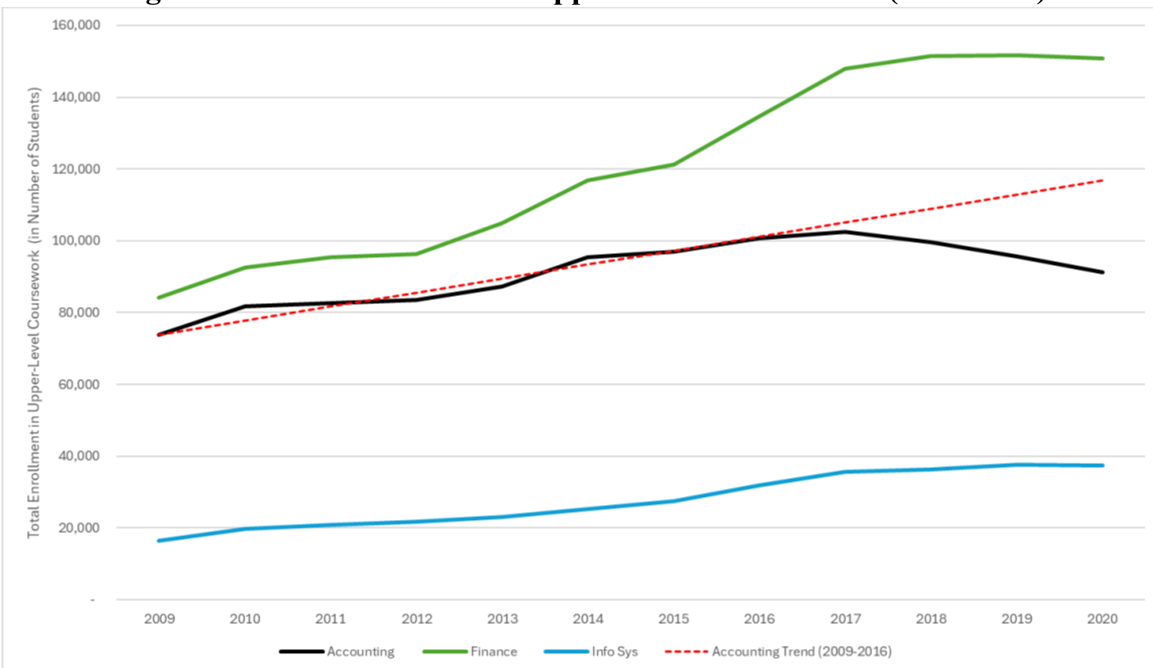
Note: This figure presents the coefficients of *ML_Exposure*Year* regressed on *Accounting.*

Figure 2: Panel B – Layoff Exposure and Incoming Accounting Majors vs. Other Groups



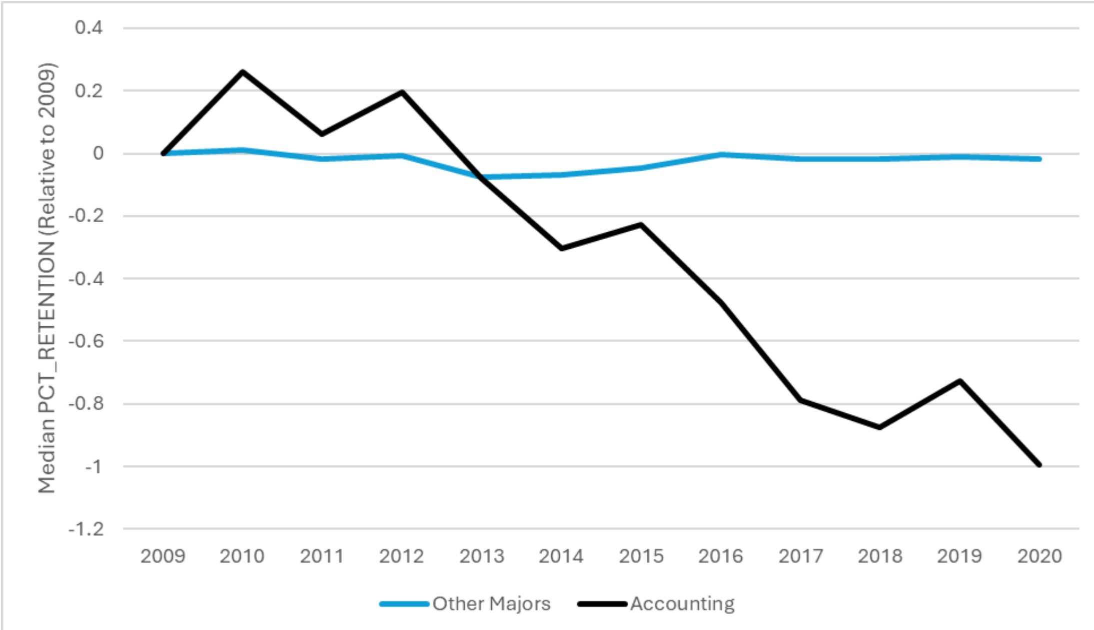
Note: This figure presents the coefficients of *ML_Exposure*Year* regressed on *Accounting, Finance* or *Technology.*

Figure 3: Total Enrollment in Upper-Level Coursework (2009-2020)



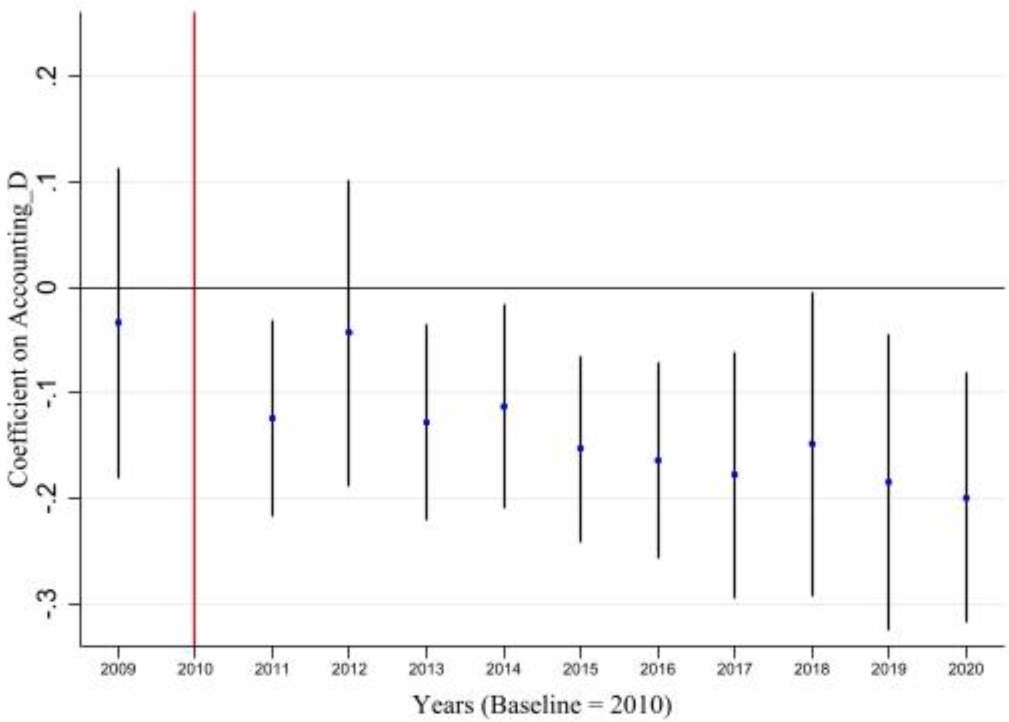
The figure presents the total enrollment in upper-level coursework between Accounting_D, Finance, and Information Systems groups from the course catalog data.

Figure 4: Panel A- Median Upper-Level Enrollment (at T) Relative to Lower-Level Enrollment (at T-2) Within Department (2009-2020)



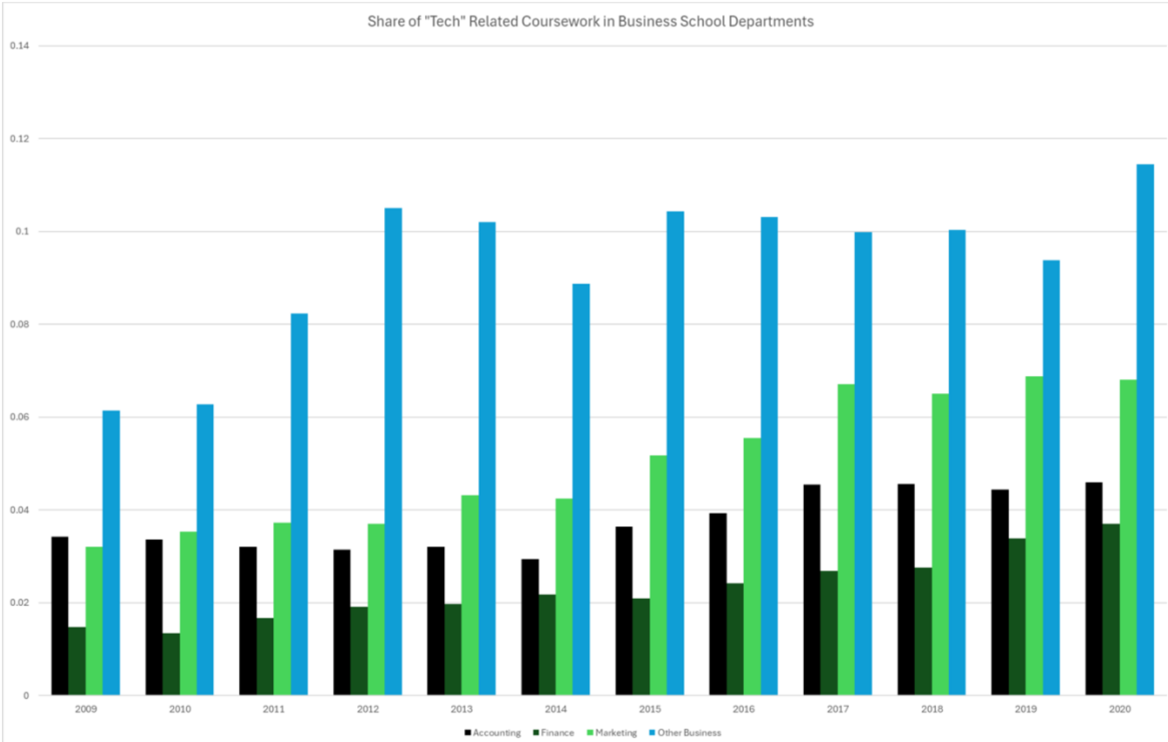
This figure presents the median Pct_Retention relative to the baseline of 2009 across Accounting_D and other departments.

Figure 4: Panel B – Event Study Estimates of Retention in Accounting (2009-2020)



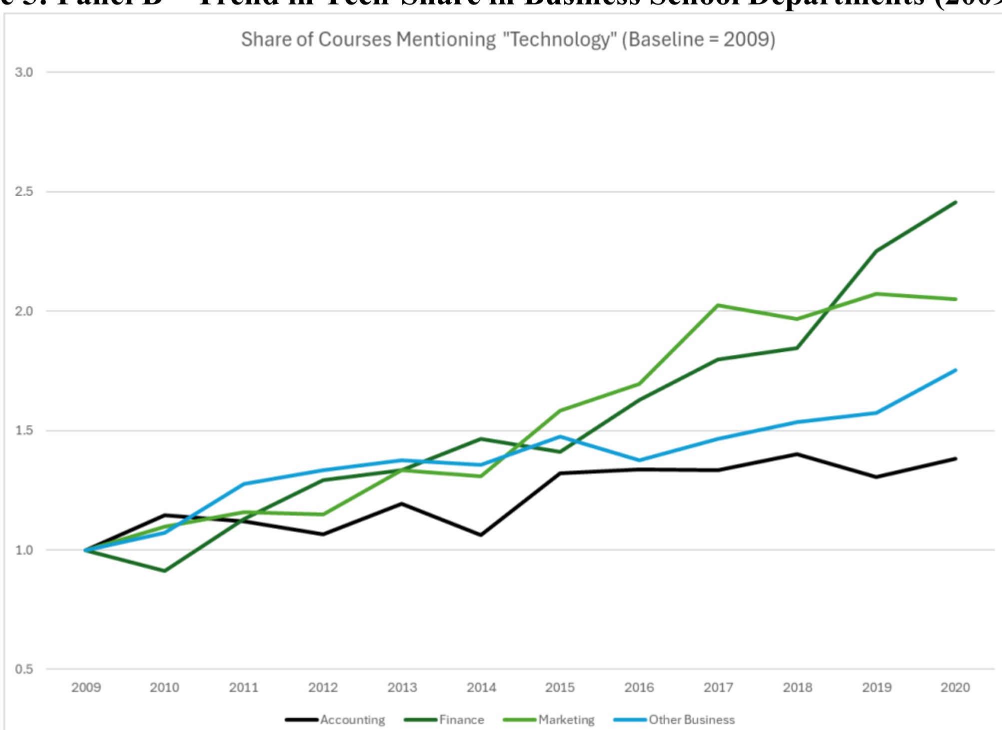
This figure presents the coefficients on *Accounting_D* interacted with yearly indicators on *Pct_Retention* relative to the baseline of 2010 across Accounting_D and other departments. This figure shows that the estimates of Eq. (6) display a steady decline through 2020.

Figure 5: Panel A – Tech-Share of Courses in Business School Departments (2009-2020)



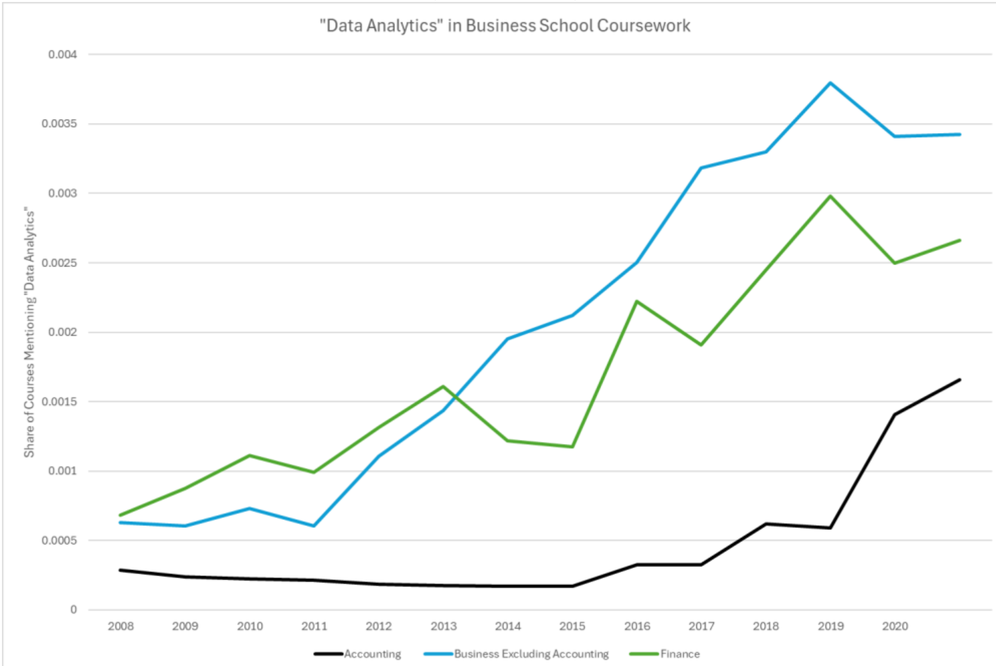
This figure presents the share of "tech" related coursework offered by Accounting, Finance, Marketing, and other business school departments between 2009 and 2020.

Figure 5: Panel B – Trend in Tech-Share in Business School Departments (2009-2020)



This figure presents the change in "tech" related coursework offered by Accounting, Finance, Marketing, and other business school departments from 2009, which is indexed to 1.

Figure 5: Panel C – "Data Analytics" Coursework in Business School Departments (2009-2020)



This figure presents the change in coursework mentioning "data analytics" between Accounting, Finance, and other business school departments from 2009. The y-axis shows the share of courses mentioning "data analytics" divided by the total number of courses offered by that department in that institution in that year.

Table 1: Most Frequent "Tech" Related Coursework by Business School Department

Finance		**Marketing**		**Business Administration**		**Accounting**	
Title	*N*	*Title*	*N*	*Title*	*N*	*Title*	*N*
financial information tech	195	digital marketing	172	business data analysis	225	actg info sys	619
fin info technolog	82	marketing research	165	strategic info technology	207	auditing	186
entrepreneurial fin computing	65	marketing analytics	153	business statistics	189	prin of managerial actg	144
financial modeling	65	strategic internet mktg	124	computers and business	176	actg info sys with lab	139
multinational finance	42	mktg comm	118	business analytics	174	prin of financial actg	139
fintech-an introduction	38	electronic mktg	116	software apps for bus prod	126	actg applications	112
trading and markets	36	digital branding	84	info studies: digitalage	126	advanced cost mgmt	92
forecasting for decision making	34	services marketing	83	managing the growth business	124	accounting info systems	83
equity markets trading	32	e-marketing	82	business data analysis ii	124	computerized actg for sb	83
short term financial mgmt.	31	supply chain mgmt	75	business communications	110	acct info sys	83
int'l bus transactions	30	sports mktg	72	information technology	108	acct inform system	82
valuation of innovation	28	marketing and technology	60	decision analysis	103	intro to actg sys	68
futures and options	28	direct& interactive mktg	60	electronic commerce	98	introduction to acc info	63
adv fin strategy	27	advertising team wkshp	52	digital branding	88	profit planning & ctrl	57
foundations of fintech	26	strat supply chain mgmt	50	tech entrepreneurship	81	info sys auditing	57
cryptocurrencies	26	saas marketing	48	practicum in computerized os	79	internal auditing	57
financial technologies	26	entrp sales & mktg	42	web and interaction design	76	accounting systems	56
finmodeling & analytics	24	internet/interactive mktg	42	information technology mgmt	75	comp audit & it ctrls	47
finance info sys	24	social media mktg	42	art and digital tools	68	info sys ctrls & audit	46
fin analysis & forecasting	22	applied mrkt research	39	business statistics	67	managerial actg	39

This table presents the most frequent courses identified as "tech" related across some business school departments, including Finance, Marketing, Business Administration and Accounting. The number corresponds to the number of observations (courses) identified with the respective course title. All variable definitions are in Appendix A.

Table 2: Sample Selection

Panel A: HERI Sample	**N**
All observations in HERI from 1995 to 2010	5,134,043
Less observations missing student's home zip code	4,595,494
Less observations missing values for college majors	4,328,269
Less observations missing values for variables in main tests	3,702,969
Less observations missing values for BLS/BEA county level variables	**2,268,877**
Panel B: Course-Level Sample	**N**
All observations at the department-year level from 2009 to 2020	120,637
Less observations missing data for enrollment or course descriptions	**105,741**

Table 3: Summary Statistics

Variable	N	Mean	SD	P25	P75
Panel A: HERI Sample					
Dependent Variables					
Accounting	2,268,877	0.024	0.154	0.000	0.000
Wage Sensitive	2,268,877	0.596	0.491	0.000	1.000
Cost Sensitive	2,268,877	0.118	0.322	0.000	0.000
Key Variables of Interest					
ML_Exposure	2,268,877	0.505	0.500	0.000	1.000
Control Variables					
Female	2,268,877	0.545	0.498	0.000	1.000
Minority	2,268,877	0.094	0.292	0.000	0.000
Firstgen	2,268,877	0.161	0.368	0.000	0.000
Income	2,268,877	5.671	3.264	1.000	9.000
HSGPA	2,268,877	6.479	1.395	1.000	8.000
GDPgl4	2,268,877	0.053	0.021	0.040	0.066
Unemploy	2,268,877	5.409	1.727	4.400	6.100
Paccounting	2,268,877	0.066	0.248	0.000	0.000
SAT_ACT	2,268,877	0.532	0.264	0.318	0.758
Other Variables					
ML_Total	2,268,877	104.000	138.000	23.304	131.242
Local Labor Force	2,268,877	13701.000	9448.000	6730.900	18846.100
ML_LF	2,268,877	0.008	0.025	0.003	0.010
AutomationRelated	2,268,877	0.081	0.273	0.000	0.000
PostCPA150	2,268,877	0.471	0.499	0.000	1.000
Panel B: Course Catalog Sample					
Dependent Variables					
Pct_Retention	105,741	0.112	1.309	-0.683	0.000
Adapt_Tech	105,741	0.297	0.457	0.000	1.000
Key Variables of Interest					
Accounting_D	105,741	0.011	0.104	0.000	0.000
Control Variables					
Business	105,741	0.044	0.157	0.000	0.000
Tech	105,741	0.082	0.275	0.000	0.000
Log Enroll	105,741	11.142	1.422	10.633	11.924
Other Variables					
Restrictive	105,741	0.519	0.500	0.000	1.000

Table 4: Are layoff-exposed students more sensitive about post-graduation wages and more worried about paying for college?

	(1) *Wage Sensitive*	(2) *Wage Sensitive*	(3) *Cost Sensitive*	(4) *Cost Sensitive*
ML_Exposure	**0.011***	**0.010***	**0.031***	**0.027***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Female		-0.064***		0.038***
		(0.000)		(0.000)
Minority		0.036***		0.044***
		(0.000)		(0.000)
Firstgen		0.022***		0.044***
		(0.000)		(0.000)
Income		0.003***		-0.023***
		(0.000)		(0.000)
HSGPA		0.005***		-0.007***
		(0.000)		(0.000)
GDPgl4		-0.118***		-0.043
		(0.003)		(0.162)
Unemploy		-0.001		-0.000
		(0.363)		(0.774)
Paccounting		0.003*		-0.007***
		(0.070)		(0.000)
SAT_ACT		-0.114***		-0.032***
		(0.000)		(0.000)
Difference (Wage v. Cost Sensitive)			**0.017***	
Chi-Squared			**(100.25)**	
University FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,268,877	2,268,877	2,268,877	2,268,877
N Pop. Weighted	10,259,172	10,259,172	10,259,172	10,259,172
Adj. R-squared	0.244	0.251	0.020	0.081

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the weighted OLS regression results of estimating the effect of *ML_Exposure* on *Wage Sensitive* and *Cost Sensitive*. All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.

Table 5: Is layoff exposure associated with the decision to major in accounting?

	(1)	(2)	(3)	(4)
	Baseline	Full Sample	Before 2001	After 2001
	Accounting	*Accounting*	*Accounting*	*Accounting*
ML_Exposure	**0.003*** **	**0.003*** **	**0.011*** **	**-0.008*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Female		-0.008***	-0.003***	-0.011***
		(0.000)	(0.008)	(0.000)
Minority		0.003***	0.005***	0.004***
		(0.002)	(0.001)	(0.003)
Firstgen		0.008***	0.008***	0.007***
		(0.000)	(0.000)	(0.000)
Income		-0.000	-0.000**	0.000
		(0.547)	(0.014)	(0.110)
HSGPA		0.004***	0.004***	0.003***
		(0.000)	(0.000)	(0.000)
GDPgl4		-0.029***	-0.019	-0.025**
		(0.003)	(0.314)	(0.025)
Unemploy		-0.001**	-0.001*	0.001**
		(0.010)	(0.053)	(0.032)
Paccounting		0.021***	0.020***	0.021***
		(0.000)	(0.000)	(0.000)
SAT_ACT		-0.015***	-0.019***	-0.013***
		(0.000)	(0.000)	(0.000)
University FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,268,877	2,268,877	1,042,457	1,226,419
N Pop. Weighted	10,259,172	10,259,172	4,713,674	5,545,498
Adj. R-sq.	0.014	0.016	0.021	0.017

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the weighted OLS regression results of estimating the effect of *ML_Exposure* on *Accounting.* All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.

Table 6: Automation-Related Layoffs vs. Other Layoff Reasons

	(1)	(2)	(3)	(4)
	Pre 2001 Sample		Post 2001 Sample	
	AutomationRelated = 1	AutomationRelated = 0	AutomationRelated = 1	AutomationRelated = 0
	Accounting	*Accounting*	*Accounting*	*Accounting*
ML_Exposure	**-0.002**	**0.011*** **	**-0.022*** **	**-0.008*** **
	(0.140)	**(0.000)**	**(0.001)**	**(0.000)**
Female	-0.003	-0.003***	-0.006**	-0.011***
	(0.164)	(0.003)	(0.022)	(0.000)
Minority	-0.002	0.005***	-0.002	0.004***
	(0.515)	(0.002)	(0.430)	(0.004)
Firstgen	0.012***	0.008***	0.006***	0.008***
	(0.000)	(0.000)	(0.004)	(0.000)
Income	-0.004*	-0.000*	0.000	-0.000
	(0.092)	(0.064)	(0.383)	(0.253)
HSGPA	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
GDPgl4	0.0977	-0.028	-0.002	-0.034***
	(0.108)	(0.159)	(0.963)	(0.012)
Unemploy	-0.004***	-0.007	-0.000	-0.001**
	(0.002)	(0.247)	(0.638)	(0.147)
Paccounting	0.014***	0.020***	0.019***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
SAT_ACT	-0.018***	-0.019***	-0.015***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Difference	**-0.013*** **		**-0.014*** **	
Chi-Squared	**(16.51)**		**(26.05)**	
University FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	86,648	955,809	101,534	1,124,885
Adj. R-sq.	0.015	0.021	0.011	0.017

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the weighted OLS regression results of estimating the effect of *ML_Exposure* on *Accounting,* where the sample is split by state-years experiencing automation-related layoffs (AutomationRelated = 1) and others. All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates

Table 7: Is Accounting Coursework Slower to Adapt to Emerging Technology?

	(1) Full Sample *Adapt_Tech*	(2) Difference *v. Business*	(3) Difference *v. Tech*
Accounting_D	**-0.046****		
	(0.029)	**-0.077*****	
Business	0.031	F stat. = 7.55	
	(0.130)		**-0.119*****
Tech	0.073***		F stat. = 26.54
	(0.000)		
Log Enroll	-0.150***		
	(0.003)		
Constant	1.968***		
	(0.000)		
University FE	Yes		
Year FE	Yes		
N	105,741		
Adj. R-squared	0.108		

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the OLS regression results of estimating the association between *Accounting_D* and *Adapt_Tech.* In Columns (2) and (3) we test for the difference in coefficients between accounting and other business or technology-related disciplines. All specifications include university and year fixed effects. We cluster standard errors by university. All variable definitions are in Appendix A. We report p-values in parentheses below coefficient estimates.

Table 8: Where is Retention in Upper-Level Accounting Coursework Falling?

	(1)	(2)	(3)	(4)	
	Full Sample	Full Sample	Adapt_Tech = 1	Adapt_Tech = 0	Difference
	Pct_Retention	*Pct_Retention*	*Pct_Retention*	*Pct_Retention*	*Pct_Retention*
Accounting_D	**-0.178*** **	**-0.120** **	**0.002**	**-0.231*** **	**0.229** **
	(0.001)	**(0.019)**	**(0.183)**	**(0.000)**	**(0.015)**
Business		0.325***	0.325***	0.324***	
		(0.000)	(0.000)	(0.000)	
Tech		0.564***	0.564***	0.564***	
		(0.000)	(0.000)	(0.000)	
Log Enroll		0.097**	0.098**	0.096**	
		(0.040)	(0.033)	(0.045)	
Constant	0.114***	-1.019*	-1.037**	-1.013*	
	(0.000)	(0.052)	(0.044)	(0.058)	
University FE	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
N	105,741	105,741	105,136	105,189	
Adj. R-squared	0.048	0.063	0.063	0.063	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the OLS regression results of estimating the association between *Accounting_D* and *Pct_Retention,* where the sample is split in Columns (3) and (4) by accounting departments adding new coursework that is "tech" related (Adapt_Tech = 1) and others. Both Columns (3) and (4) include all observations from non-accounting departments. All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.

Table 9: Does Restrictive Licensing Contribute to Slow Adaptation to Technology?

	(1) Full Sample *Adapt_Tech*	(2) Restrictive = 1 *Adapt_Tech*	(3) Restrictive = 0 *Adapt_Tech*	Difference *Adapt_Tech*
Accounting_D	**-0.046****	**-0.054****	**-0.037**	**-0.017**
	(0.029)	**(0.040)**	**(0.281)**	**(0.676)**
Business	0.031	-0.010	0.069**	
	(0.130)	(0.683)	(0.029)	
Tech	0.073***	0.074***	0.072***	
	(0.000)	(0.000)	(0.000)	
Log Enroll	-0.150***	-0.106	-0.200***	
	(0.003)	(0.157)	(0.001)	
Constant	1.968***	1.479*	2.487***	
	(0.000)	(0.082)	(0.000)	
University FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
N	105,741	54,542	51,199	
Adj. R-squared	0.108	0.093	0.125	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the OLS regression results of estimating the association between *Accounting_D* and *Adapt_Tech,* where the sample is split in Columns (2) and (3) by state-years requiring more than the median number of accounting credit hours for CPA licensure (Restrictive = 1) and others. All specifications include university and year fixed effects. We cluster standard errors by university. All variable definitions are in Appendix A. We report p-values in parentheses below coefficient estimates.

Table 10: Does Restrictive Licensing Contribute to Retention Declines?

	(1) Full Sample *Pct_Retention*	(2) Restrictive = 1 *Pct_Retention*	(3) Restrictive = 0 *Pct_Retention*	Difference *Pct_Retention*
Accounting_D	**-0.120****	**-0.243*****	**0.026**	**-0.269*****
	(0.019)	**(0.002)**	**(0.122)**	**(0.006)**
Business	0.325***	0.174**	0.466***	
	(0.000)	(0.050)	(0.000)	
Tech	0.564***	0.509***	0.631***	
	(0.000)	(0.000)	(0.000)	
Log Enroll	0.097**	0.087	0.108**	
	(0.040)	(0.272)	(0.017)	
Constant	-1.019*	-0.840	-1.217**	
	(0.052)	(0.350)	(0.014)	
University FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
N	105,741	54,542	51,199	
Adj. R-squared	0.063	0.048	0.075	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the OLS regression results of estimating the association between *Accounting_D* and *Pct_Retention,* where the sample is split in Columns (2) and (3) by state-years requiring more than the median number of accounting credit hours for CPA licensure (Restrictive = 1) and others. All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.

APPENDIX A: VARIABLE DEFINITIONS

Variable Names	Definition	Source
Dependent Variables		
HERI Sample		
Accounting	An indicator variable equal to 1 for students who plan to major in accounting and 0 otherwise; using responses to the HERI prompt: "Below is a list of different undergraduate major fields grouped into general categories. Mark only one oval to indicate your probable field of study." Construction of this variable is explained in detail in Appendix B.	HERI
Wage Sensitive	An indicator variable equal to 1 for students who answered, "very important" to the question "In deciding to go to college, how important is the ability to make more money"" and 0 otherwise. Responses were on a three-point scale (1 = not important, 2 = somewhat important, or 3 = very important). HERI variable is called "*reason06*".	HERI
Cost Sensitive	An indicator variable equal to 1 for students who answered "Major" to the question "Do you have any concern about your ability to finance your college education" and 0 otherwise. Responses were on a three-point scale (1 = None, 2 = Some, or 3 = Major). HERI variable is called "*fincon*".	HERI
Finance	An indicator variable equal to 1 for students who plan to major in finance and 0 otherwise; using responses to the HERI prompt: "Below is a list of different undergraduate major fields grouped into general categories. Mark only one oval to indicate your probable field of study."	HERI
Technology	An indicator variable equal to 1 for students who plan to major in technology-related majors and 0 otherwise; using responses to the HERI prompt: "Below is a list of different undergraduate major fields grouped into general categories. Mark only one oval to indicate your probable field of study." The list of majors includes Computer Science (*No. 663*), All Engineering Majors (*No. 400-558*) and Data Processing or Computer Programming (*No. 1002*).	HERI
Other Business	An indicator variable equal to 1 for students who plan to major in business majors other than accounting and 0 otherwise; using responses to the HERI prompt: "Below is a list of different undergraduate major fields	HERI

Variable Names	Definition	Source
	grouped into general categories. Mark only one oval to indicate your probable field of study."	
Course-Level Sample		
Adapt_Tech	An indicator variable equal to 1 for a department-year within a university if the share of upper-level coursework containing the phrases or words like "technologies", "software", "technology" increased from the previous year. Construction of this variable is explained in detail in Appendix B.	Course Catalogs
Pct_Retention	A continuous variable that equals the difference between upper-level enrollment in a department at year *t* and lower-level enrollment in the same department at year *t-2*, divided by the lower-level enrollment at year *t-2*. *Pct_Retention* is winsorized at 1% and 99%. Construction of this variable is explained in detail in Appendix B.	Course Catalogs
Key Variables of Interest		
HERI Sample		
ML_Exposure	An indicator variable equal to 1 for students who, in the year before their freshman year in college, were exposed to mass layoffs more than the median student in the state. We first construct a continuous measure of layoff exposure which is equal to the sum of people laid off in mass layoff events in each county-year in our sample. We then divide this sum by the number of people in the local labor force to get a percentage of local workers directly impacted by a mass layoff event. We then merge this county-year mass layoff percentage with individuals in HERI, matching by the county of their home address and by the year before they enter college. Finally, we calculate the median value of this continuous measure of layoff exposure across our sample of HERI students within each state-year and assign a value of 1 when this continuous measure of layoff exposure is greater than the state-level median. Construction of this variable is explained in detail in Appendix B.	BLS
Course-Level Sample		
Accounting_D	An indicator variable equal to 1 for accounting departments and 0 otherwise.	Course Catalogs
Business	An indicator variable equal to 1 for all business school departments other than accounting, and 0 otherwise.	Course Catalogs
Tech	An indicator variable equal to 1 for all computer science and engineering departments and 0 otherwise.	Course Catalogs

Variable Names	**Definition**	**Source**
Log Enroll	Equals Log(1+Enrollment), where Enrollment is defined as the sum of students enrolled in coursework at a university at year *t*.	Course Catalogs
Restrictive	An indicator variable equal to 1 for state-years where *PostCPA150 = 1* and the number of accounting credit hours required by the state CPA board is above the national median (24).	Course Catalogs
Control Variables		
Female	An indicator variable equal to 1 for female students, 0 otherwise; from a HERI prompt requesting "Your sex" and offering the options "Male" and "Female."	HERI
Minority	An indicator variable equal to 1 for students whose race is Black, Native American, or Hispanic, 0 otherwise; from a HERI prompt requesting race/ethnicity data using the prompt "Are you: (Mark all that apply)" and listing between seven and nine race/ethnicity categories.	HERI
Firstgen	An indicator variable equal to 1 for first generation college students, 0 otherwise.	HERI
Income	A value from 1 to 10 indicating the decile rank in a given year of a student's parents' income (as reported by the student).	HERI
HSGPA	A value from 1 to 8 indicating a given student's average grade in high school (as reported by the student).	HERI
GDPgl4	The annual percentage change in the GDP of the state in which a student's permanent/home address is located, averaged from year *t* to year *t* – 3.	HERI
Unemploy	The unemployment rate in year *t* in the state in which a student's permanent/home address is located.	BLS
Paccounting	An indicator variable equal to 1 for students with at least one parent whose occupation is "accountant or actuary," 0 otherwise; from HERI prompts requesting the occupation of each of the student's parents and listing 46 occupational categories.	HERI
SAT_ACT	A measure of a student's relative performance on standardized tests using responses to the HERI question "What were your scores on the SAT I and/or ACT?." HERI reports one, two, three, or four test scores for each student (ACT composite score, SAT verbal, SAT writing, and SAT math). Our measure is the mean of a student's within-year percentile rank on all the test scores they reported.	HERI
Other Variables		

Variable Names	**Definition**	**Source**
ML_Total	The number of workers laid off in "extended mass layoffs" at the student's local area (county) in the year prior to college, identified by initial claimants of unemployment insurance associated with mass layoff events. Data is from Mass Layoff Statistics program from the Bureau of Labor Statistics. Construction of this variable is explained in detail in Appendix B.	BLS
Local Labor Force	The number of workers identified to be part of the labor force at the student's local area (county) in the year prior to college. Data is from the Local Area Unemployment Statistics by the Bureau of Labor Statistics. Construction of this variable is explained in detail in Appendix B.	BLS
ML_LF	Equals ML_Total/Local Labor Force, winsorized at 1% and 99%. In other words, this variable represents layoff exposure for the student in the year prior to college as a share of the locality's (county) labor market size. Construction of this variable is explained in detail in Appendix B.	BLS
Log Mass Layoffs	Equals Log(1+ML_Total)	BLS
ML_Top10	An indicator variable equal to 1 if *ML_LF* is in the top decile of the country in the year preceding their freshman year in college. The variable is constructed similar to *ML_Exposure*, which is explained in detail in Appendix B.	BLS
AutomationRelated	An indicator variable equal to 1 for students exposed to mass layoffs *because of automation-related reasons* in their home state. Equals 1 if the student's home state included at least one mass layoff event related to "Automation/technological advance" "*R005*") in the year prior to college as identified by Mass Layoffs State-Year dataset. The list of states includes Alaska, Indiana, Iowa, Kansas, Minnesota, Mississippi, New Mexico, North Dakota, Oklahoma, and South Dakota. Construction of this variable is explained in detail in Appendix B.	BLS
PostCPA150	An indicator variable equal to 1 for students from state-years after the introduction of the 150-hour rule for the CPA. (Barrios 2022; Sutherland, Uckert, and Vetter 2024)	N/A

APPENDIX B: CONSTRUCTION OF KEY VARIABLES

B1. Measuring Quantity of Incoming Students

To study incoming first-year students' college major choices, we use a large-sample survey of college first-year students produced by the Higher Education Research Initiative (HERI) and has been used in prior accounting research (Carnes, Christensen, and Madsen 2023; Le 2024; Leiby and Madsen 2017; Madsen 2015). The HERI sample contains information on approximately 2.3 million students' demographics, socio-economic status, stated preferences about intended majors, concerns related to paying for college, home zip code and parental occupation. This survey is conducted "*before students start their college careers and is available as early as mid-April and as late as October. Most campuses conduct the survey during orientation and allow about one hour for survey administration*" (HERI 2024). We construct an indicator variable, *Accounting*, which equals 1 for students who plan to major in accounting and 0 otherwise and use this as our primary dependent variable, similar to Le (2024) and Carnes, Christensen, and Madsen (2023).

B2. Measuring Layoff Exposure

The Mass Layoffs Statistics program of the BLS tracks major job cutbacks using data from state unemployment insurance databases. BLS defines a "mass layoff" as any event where 50 or more initial claims for unemployment insurance benefits being filed against a particular employer during a 5-week period.[26] BLS reports these data at the county level starting from the year ending March 1995. We use the number of initial claimants associated with mass layoff events for a given county in a given year and call this variable *ML_Total.* Next, we use data from the Bureau of Economic Analysis (BEA)'s Local Area Unemployment Statistics to obtain a given county's labor

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[26] The BLS obtains information on the total number of workers separated during the mass layoffs, including the workers who do not file for unemployment insurance, and the reasons for these separations according to the employer. These layoffs involve both people subject to recall and those who are terminated. The program operated from 1995 to the first quarter of 2013.

force and call this *Local Labor Force.* We divide *ML_Total* by *Local Labor Force* to calculate the share of a county's labor force impacted by mass layoff events to better approximate the salience of these layoff events in a given year in a given county and call this variable *ML_LF.*[27]

As reported in Table 3, the mean value of *ML_Total* is 104 compared to the mean value of *Local Labor Force* of 13,701 suggesting that on average, annual mass layoff events affect up to 0.8% of the local labor market. We note that *ML_LF* has an average of 0.008, which is close to the 75th percentile value of 0.010, indicating the presence of significant skew to the right even after winsorization. For a visual representation of the skew, see Figure C1 Panel B in Appendix C. Given the presence of this skew, our primary variable is specified as an indicator variable to avoid biasing OLS estimates from extreme values of *ML_LF.* For instance, we classify students from county-years above the state-year median of *ML_LF* to identify cohorts of students that are incrementally more exposed to layoffs after accounting for regional economic trends. For example, the state-year median value of *ML_LF* for California in the year 1993 was 0.005, meaning annual mass layoff events affected 0.5% of the labor force on average. *ML_Exposure* will equal 1 for students starting college in 1994 who are from California counties that had annual mass layoff events that affected more than 0.5% of the labor force, and 0 for students from other California counties.

We plot the geographic variation in *ML_LF* over time in Figure C1 Panel A, and the kernel density of *ML_LF* across years in Figure C1 Panel B. The geographic variation in *ML_LF* in any given year is noticeable, suggesting that *ML_LF* captures more than just national business cycle fluctuations (Blom, Cadena and Keys 2021) and even state-level economic trends (Carnes, Christensen, and Madsen 2023), because within-state variation in layoff exposure in a given year

[27] We winsorize *ML_LF* at 1% and 99%.

depends on local factors like the presence of specific firms, industries, and worker skill compositions, all of which may be differently exposed to economic uncertainty, and to a certain extent, automation. Figure C1 Panel A plots values of *ML_LF* on county-level maps of the US over time and shows that it varies substantially across counties within states and over time. The substantial within-state variation means that state-level measures of economic trends are likely poor proxies for exposure to local mass layoffs. In addition, while there is wide variation in the locations of mass layoffs over time, the total quantity of mass layoffs nationally is fairly even over time as evidence by the substantial overlap in the year-by-year kernel densities in Figure C1 Panel B. This suggests that variation in national business cycles over time likely captures only a small subset of the variation in underlying economic uncertainty driven by exposure to mass layoffs.

A limitation of our data is that we cannot directly observe preferences for economic security at the student level. To proxy for this construct, we merge the county-year level measure of layoff exposure (*ML_LF*) to the HERI sample based on the student's home address[28] and the year of the survey. Given the timing of the layoff measurement by BLS, we merge the layoff measure by county-year for the year ending in March of year *t* for student responses recorded by October of year *t.* To mute the effects of skewed *ML_LF* values[29] and for ease of interpretation, we discretize the measure of *ML_LF* into *ML_Exposure,* which is an indicator variable that equals 1 if a given student is exposed to a value of *ML_LF* that is above the state-year's median and use this as our main operationalized measure of layoff exposure.

B3. Automation-Related Layoffs

[28] We use ZIP code-county crosswalks published by Census to merge the two datasets.

[29] Panel B also shows that the distribution of *ML_LF* is skewed to the right even after winsorization, implying that relatively few county-years have large exposure to layoffs as a share of their labor force, which may induce sensitivity to extreme observations and may produce heteroskedastic standard errors in an OLS regression if used without scaling or standardization (Angrist and Pischke 2009). In Appendix C, we use a continuous measure of layoff exposure and confirm that our results are directionally and statistically consistent with our main findings and year-by-year analyses.

BLS records "reasons" for mass layoff events that include "Automation/technological advance", which they report as a count at the state-year level. We investigate the coefficient on *ML_Exposure* from Equation (3) in a sample split by *AutomationRelated*, which is an indicator variable equal to 1 if a student's home state included at least one mass layoff event related to automation or technological advances in the year prior to college as recorded by the BLS.[30] Students exposed to mass layoffs, i.e., for whom *ML_Exposure* equals 1 in *AutomationRelated* state-years are more likely to be anxious about automation,[31] and therefore even less likely to major in accounting when compared to students exposed to mass layoffs in other state-years.

B4. Measuring Retention in Upper-Level Coursework

We define retention in upper-level coursework as *Pct_Retention* which is the difference in enrollment between upper-level coursework (typically taken in the 3rd year and above) at year t and lower-level coursework (typically taken in the first two years of college) at year t-2 scaled by the lower-level enrollment at t-2 for a department in year t.

For an accounting department, *Pct_Retention* may include almost all business school students in the denominator, and only accounting majors, accounting minors or those who choose accounting electives in the numerator. Therefore, a reduction in *Pct_Retention* over time may imply that among business school students within a department exposed to accounting coursework, the percentage of students that filter through to either major, minor, or take accounting electives has declined. Additionally, we study enrollment in upper-level accounting coursework relative to lower-level coursework within a university over time, which should mitigate concerns about differences in major requirements or business school divisional requirements across universities.

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30 Approximately 8.1% of students in the sample were from state-years with at least one mass layoff event labeled with a reason of "Automation/technological advances."

31 Mass layoff events are usually covered by local media and usually contain the reason for layoffs. For examples, refer to Section 2.1.

In Figure 4, we plot the median values of *Pct_Retention* across years for accounting departments and for other departments relative to 2009. The median *Pct_Retention* for all other departments stays relatively flat for the sample period between 2009-2020, whereas the median *Pct_Retention* for accounting departments falls by approximately 95%, i.e., the median *Pct_Retention* for accounting departments is -0.19 in 2009, indicating that only 19% of students who took lower-level accounting classes at the median department did not enroll in upper-level coursework. *Pct_Retention* fell to -0.38 by 2020, indicating that almost 38% of students who took lower-level accounting classes at the median department did not enroll in upper-level accounting coursework, which includes majors, minors, and those that enroll in electives. Meanwhile *Pct_Retention* stayed relatively constant across other departments in 2009-2020.

B6. *Measuring adaptation to technology*

In Panel B of Figure 5, we plot the relative trends in the share of courses within a department that mention technology across business school departments like accounting, finance, marketing, and all other business majors. Relative to a baseline of 2009, the share of "technology" related accounting coursework has increased on average by 30%, but has lagged behind finance, marketing, and other business majors in adapting to emerging technologies.

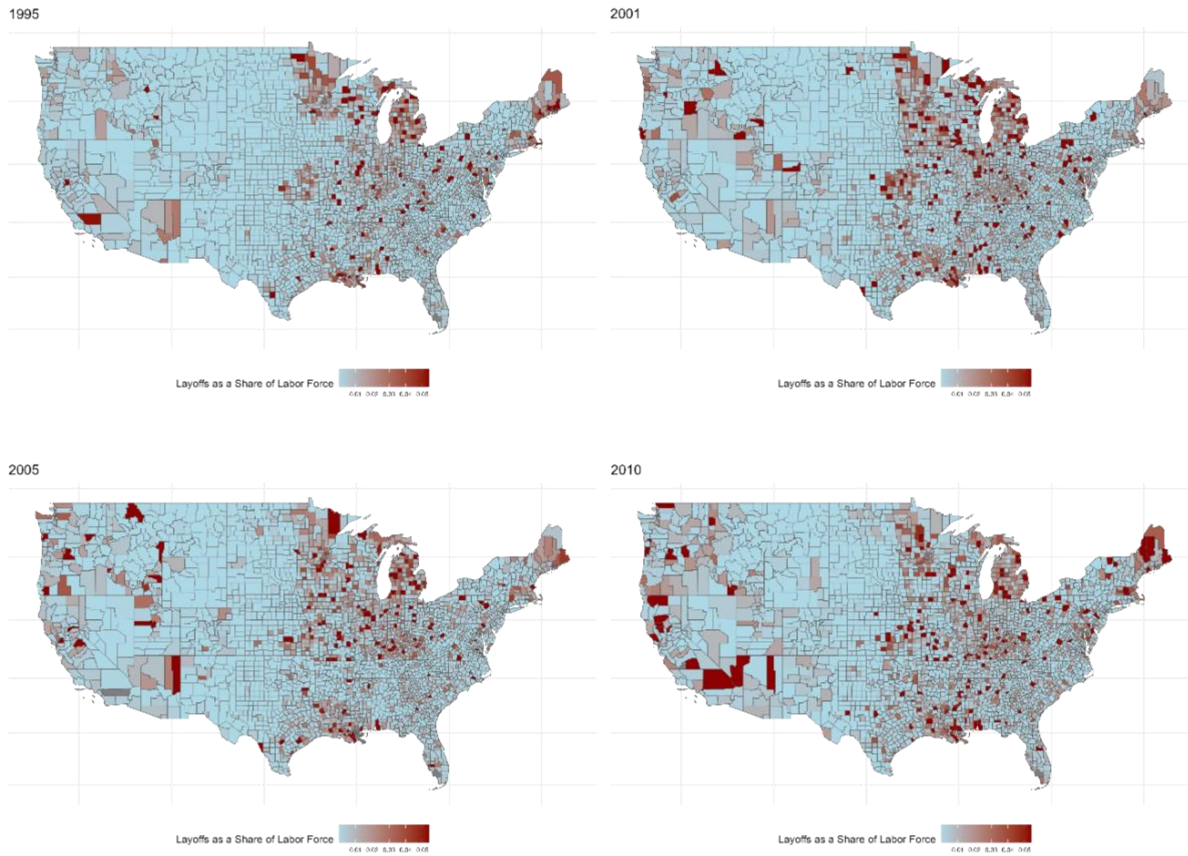
For illustrative purposes, we also identify coursework across business school departments mentioning phrases specifically related to "data analytics"[32] and plot the share of courses related to "data analytics" from 2009-2020 in Panel C of Figure 5. The changes in the share of courses are similar to Panel B of Figure 5, where accounting lags behind other business school departments in adding course content related to emerging technologies demanded by professional labor markets.

[32] We use the regular expression "\b(?:data\s+(?:analyz(?:e|ing|ed))|analyz(?:e|ing|ed)\s+data)\b" which identifies courses that mention variations of phrases related to data analytics.

To identify department-years that are adapting to technology, we define *Adapt_Tech* as an indicator variable that equals 1 for a department-year if the share of upper-level coursework in the department related to technology increases from the prior year.

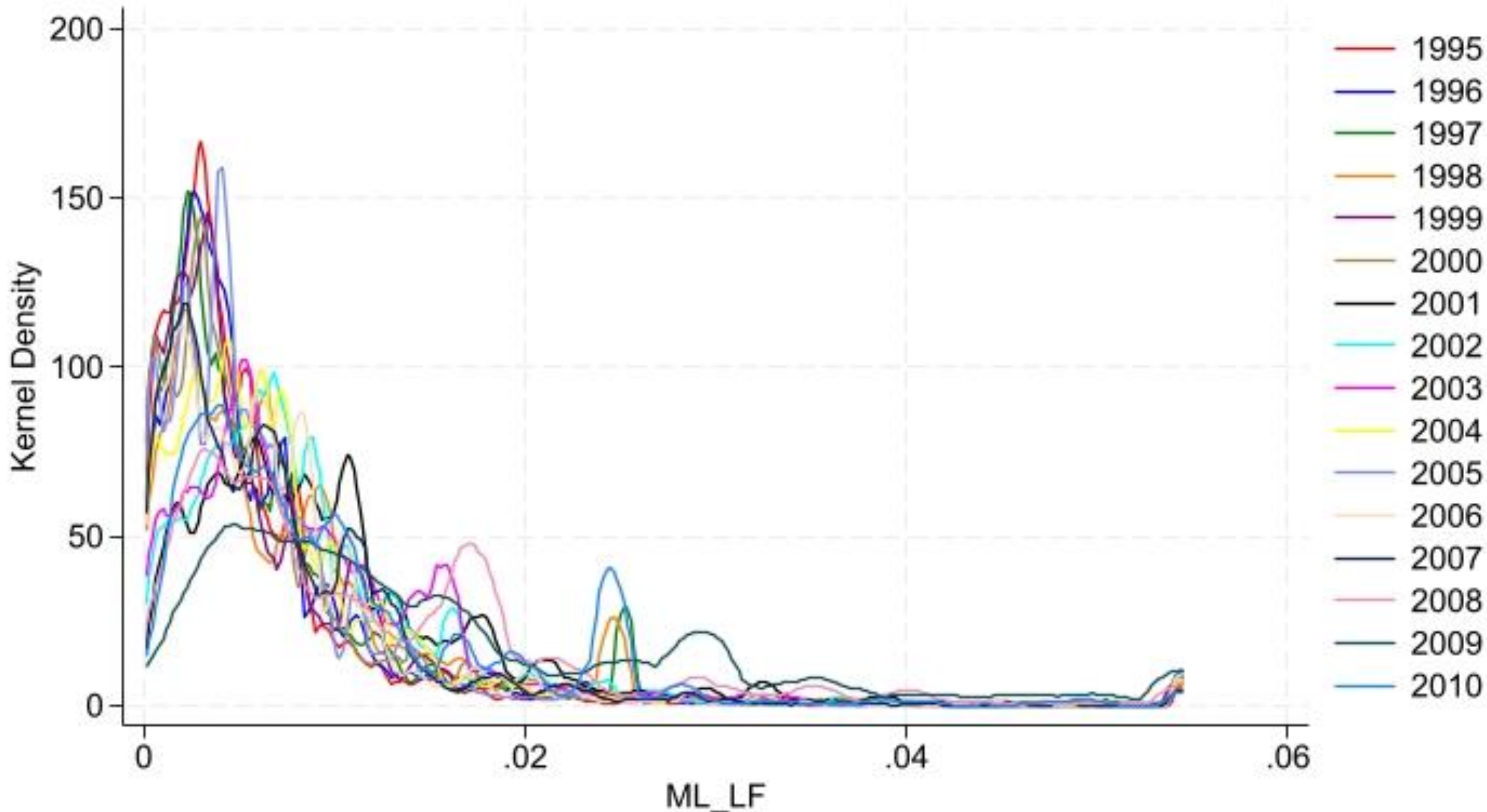
APPENDIX C: ADDITIONAL TABLES AND FIGURES

Figure C1: Panel A – Geographic Variation in Local Layoff Exposure (1995-2010)



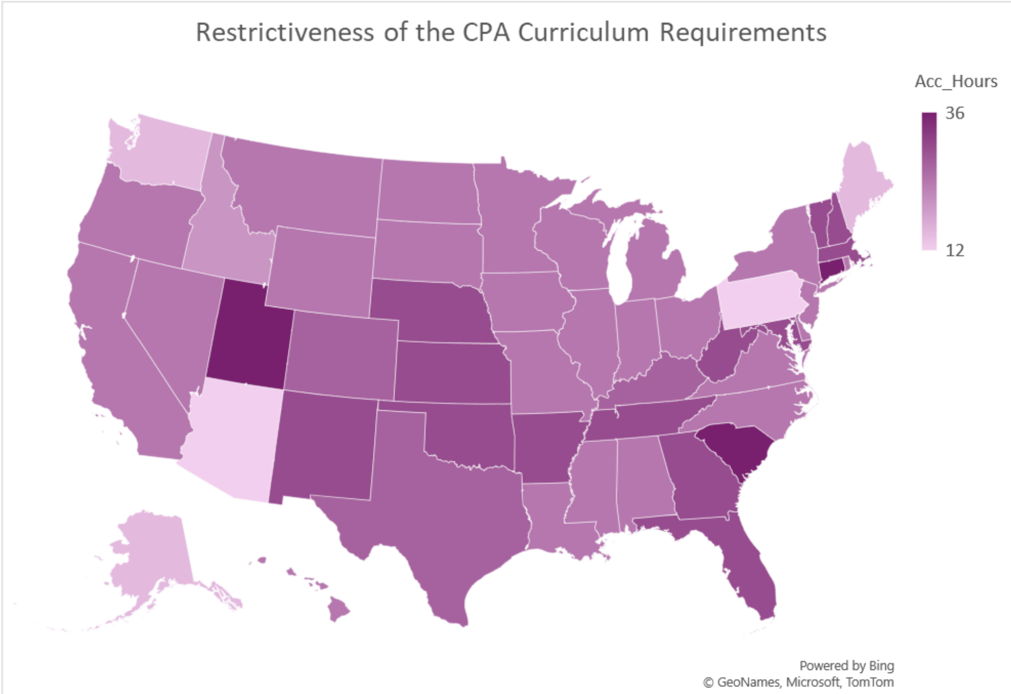
Note: This figure presents the extent of layoff exposure as a share of local labor force (*ML_LF)* at the county level in the US for select years between 1995 and 2010. Each subfigure represents the value of *ML_LF* for the period between March of the preceding year to March of the year immediately before a students' first semester of college for the calendar years of 1996, 2001, 2005 and 2010.

Figure C1: Panel B – Density of Local Layoff Exposure by Year (1995-2010)



Note: This figure displays the kernel density of *ML_LF* where each line corresponds to each year of the sample.

Figure C2: Intensive and Extensive Margins of Occupational Licensing Standards by State



This figure presents the map of the United States based on the year of the introduction of the 150-hour rule (Panel A) and the number of accounting credit hours required by each state (Panel B).

Table C1: Alternative Measures of Layoff Exposure

	(1) Sample *Accounting*	(2) Pre 2001 *Accounting*	(3) Post 2001 *Accounting*	(1) Sample *Accounting*	(2) Pre 2001 *Accounting*	(3) Post 2001 *Accounting*	(1) Sample *Accounting*	(2) Pre 2001 *Accounting*	(3) Post 2001 *Accounting*
ML_Exposure	**0.003*** **	**0.011*** **	**-0.008*** **						
	(0.000)	**(0.000)**	**(0.000)**						
Log Mass Layoffs				**0.001*** **	**0.003*** **	**-0.001** **			
				(0.000)	**(0.000)**	**(0.011)**			
ML_Top10							**0.006*** **	**0.017*** **	**-0.013*** **
							(0.000)	**(0.000)**	**(0.000)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,268,877	1,042,457	1,226,419	2,268,877	1,042,457	1,226,419	2,268,877	1,042,457	1,226,419
N Pop. Wg.	10,259,172	4,713,674	5,545,498	10,259,172	4,713,674	5,545,498	10,259,172	4,713,674	5,545,498
Adj. R-sq.	0.016	0.021	0.017	0.016	0.021	0.017	0.016	0.021	0.017

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the weighted OLS regression results of estimating the effect of *ML_Exposure* and alternative measures of layoff exposure *Log Mass Layoffs and ML_Top10* on *Accounting.* All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.

Table C2: Layoff Exposure as an Instrument for Wage and Cost Sensitivity

Panel A: Wage Sensitivity

	(1)	(2)	(3)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample	Pre 2001	Post 2001	Sample	Pre 2001	Post 2001	Sample	Pre 2001	Post 2001
	Accounting	*Accounting*	*Accounting*	*Wage Sensitive*	*Wage Sensitive*	*Wage Sensitive*	*Accounting*	*Accounting*	*Accounting*
Wage Sensitive	**0.000****	**0.010*****	**-0.010*****						
	(0.030)	**(0.000)**	**(0.000)**						
ML_Exposure				0.010***	0.011***	0.009***			
				(0.000)	(0.000)	(0.000)			
$\widehat{Wage\ Sensitive}$							**0.254*****	**0.365*****	**-0.133*****
							(0.000)	**(0.000)**	**(0.000)**
Wald F-Stat				63.62	34.82	40.00	63.62	34.82	40.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,268,877	1,042,457	1,226,419	2,268,877	1,042,457	1,226,419	2,268,877	1,042,457	1,226,419
N Pop. Wg.	10,259,172	4,713,674	5,545,498	10,259,172	4,713,674	5,545,498	10,259,172	4,713,674	5,545,498
Adj. R-sq.	0.016	0.021	0.017	0.016	0.021	0.017	0.016	0.021	0.017

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents weighted OLS regression results of estimating the effect of *Wage Sensitive* on *Accounting* in Columns (1)-(3), first-stage regressions results in Column (3)-(5), and 2SLS results in Columns (6)-(8). All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.

Panel B: Cost Sensitivity

	(1) Sample *Accounting*	(2) Pre 2001 *Accounting*	(3) Post 2001 *Accounting*	(3) Sample *Cost Sensitive*	(4) Pre 2001 *Cost Sensitive*	(5) Post 2001 *Cost Sensitive*	(6) Sample *Accounting*	(7) Pre 2001 *Accounting*	(8) Post 2001 *Accounting*
Cost Sensitive	**0.000*** **	**0.003*** **	**-0.002*** **						
	(0.000)	**(0.000)**	**(0.000)**						
ML_Exposure				0.027***	0.038***	0.020***			
				(0.000)	(0.000)	(0.000)			
$Cost\ \widehat{Sensitive}$							**0.126*** **	**0.209*** **	**-0.070*** **
							(0.000)	**(0.000)**	**(0.000)**
Wald F-Stat				172.82	127.45	89.05	172.82	127.45	89.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,268,877	1,042,457	1,226,419	2,268,877	1,042,457	1,226,419	2,268,877	1,042,457	1,226,419
N Pop. Wg.	10,259,172	4,713,674	5,545,498	10,259,172	4,713,674	5,545,498	10,259,172	4,713,674	5,545,498
Adj. R-sq.	0.016	0.021	0.017	0.016	0.021	0.017	0.016	0.021	0.017

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. This table presents the weighted OLS regression results of estimating the effect of *Cost Sensitive* on *Accounting* in Columns (1)-(3), first-stage regressions results in Column (3)-(5), and 2SLS results in Columns (6)-(8). All specifications include university and year fixed effects. We cluster standard errors by university. We detail all variable definitions in Appendix A. We report p-values in parentheses below coefficient estimates.