Technological Investment and Accounting: A Demand-Side Perspective on Accounting Enrollment Declines*

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Abstract

Recent years have seen a stark decline in the share of business school undergraduates majoring in accounting. We help explain this decline by empirically showing that technological development, and corporate software investment in particular, is associated with lower employment and wage growth for accounting majors than for other business majors, especially finance. Accounting majors with a technology minor fare better, while older workers fare worse, on average. As the wage gap between finance and accounting majors grows, fewer students subsequently choose an accounting major and more choose a finance major. Our evidence is consistent with recent theories of technologies having both labor-saving and labor-augmenting effects, and in which these effects vary across jobs and workers and affect human capital investments.

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1 Introduction

Accounting education is at a crossroads. Fewer students are majoring in accounting, leading to program cuts at universities and pipeline problems for firms seeking to hire graduates conversant in the language of business. Professional associations and pundits have suggested a range of causes (Financial Times 2022; AICPA 2023; Wall Street Journal 2023). These groups have broadly pointed to a supply shortage of accountants, perhaps due to low pay, licensure requirements including the 150-hour rule, limited enthusiasm for accounting, or changing work-life-balance preferences. Highlighting both pay and entry barriers, a recent Financial Times article was titled "US Accountants: Higher pay is the solution, not lower standards" (Financial Times 2023). The implications of declining accounting enrollments for employers, students, universities, and our understanding of the accounting labor market depend on what drives the decline.

We provide evidence that the decline may be a natural response to decreased *demand* for accounting labor. Labor market returns to human capital (i.e., future wages) are a primary source of incentives to invest in human capital (i.e., whether to major in accounting) (Roy 1951; Goldin and Katz 2009; Deming and Noray 2020). In this paper, we document the decline in accounting enrollment and link it to changes in the labor market returns to accounting education. We show in particular that ongoing technological developments are associated with softer demand for accountants, as reflected in both employment and wages.

To motivate and guide our analysis, we draw on recent labor economics frameworks put forward by Kogan et al. (2023; KPSS) and Acemoglu and Restrepo (2018; AR). KPSS show how the effects of technology on labor demand depend on the degree to which they are labor-saving versus labor-augmenting for the tasks a worker is responsible for. AR illustrate how technological advances can both displace and reinstate labor in the production process. Labor-saving technologies directly displace workers, lowering labor demand and wages (e.g., by automating mundane accounting tasks such as receivables tracking or consolidation). While not focused on accounting in particular, AR note that "white-collar workers in accounting… and some managerial occupations are seeing some of the tasks they used to perform being replaced by specialized software and artificial intelligence." However, accountants can simultaneously benefit from labor-augmenting technologies (e.g., doing more with less or moving from account verification into value-added advisory services), facilitating increased demand and, in AR's terminology, reinstatement.

Empirically, we first document recent trends in accounting education. Figure 1 shows that the share of business school graduates with accounting majors has declined significantly since around 2015, in line with substantial coverage in the business press. Over our sample period (extending back to 1990), while the share of accounting majors has declined, the share of finance majors—a natural alternative program for those considering accounting—has grown. In 1990, 22% of undergraduate business school graduates were accounting majors and 10% were finance majors. By 2021, 16% of business school graduates were finance majors, while just 14% were accounting majors. In fact, 2021 was the first year in our data with more finance than accounting majors. Moreover, during the recent decade's accounting major share decline, median wages for accounting majors went from being about $5,000 below median wages for finance majors to $17,000 below. These patterns motivate our regression analyses of employment levels and pay.

Building on KPSS and AR, we examine how employment (i.e., number of jobs) and wages for accounting, finance, and other business majors evolve with private sector technological investment, using software spending as a proxy. Software spending is well suited for our study, as business software is likely to be labor-saving for low-complexity accounting tasks, and labor-augmenting for high-complexity accounting tasks. Using Census data on individual workers and

BEA data on software spending, we model jobs and wages for accounting and finance majors as functions of software spending in a sector, using jobs and wages for other business majors as a benchmark. Our research design helps us establish a unique role for technology affecting labor demand, separate from the oft-cited supply-side forces noted above.

Our main finding is that increased technological investment in a sector has rather distinct effects on accounting majors. As software spending grows, accounting major employment grows, but at a far slower rate than for other business majors, or especially, finance majors. Economically, increasing software investment by 11% (the typical year-over-year growth rate in our sample) raises the industry's accounting major employment by just 0.8%, versus 1.7% for other business majors and 2.4% for finance majors. While our empirical evidence is naturally backwards-looking, the forward-looking implications are clear, as accounting jobs are expected to be among the most exposed to advances in cutting-edge technologies involving artificial intelligence and large language models (Eloundou et al. 2023).

Of course, accounting employment softness could stem from supply shortages or demand weaknesses. To help disentangle, we study wages, which should evolve differently under supply- and demand-driven explanations.[1] A negative supply shock (e.g., regulatory barriers to entering the profession) should lead to higher wages, all else equal. In contrast, a demand shock (e.g., technological replacement of accounting human capital) would tend to shift wages down. We find that wages follow a similar pattern as employment: as software spending grows, pay rises for finance majors and weakly declines for accounting majors. Collectively, these results indicate that as firms develop their technological resources and capabilities, they identify ways to automate

[1] A recent presentation at the 2023 PCAOB Conference on Auditing and Capital Markets by PCAOB Chief Economist Martin Schmalz highlighted the importance of taking a labor market equilibrium perspective when considering the potential causes of the decline in accountants.

accounting tasks, thus reducing their demand for certain types of accounting labor. The dominant effects of information technology in our sample are consistent with labor-saving technology leading to displacement of some accounting jobs.

To bolster this inference, we conduct several tests aimed at addressing alternative explanations for our wage results. First, we add state-year fixed effects to our specification, such that we compare individuals operating under the same CPA licensing regime (e.g., whether the state has adopted the 150-hour rule, its continuing education requirements, etc.). Second, we control for equipment investment, to mitigate concerns that the wage patterns derive from overall economic growth and investment opportunities rather than technology adoption specifically. Third, we implement a triple difference estimator, effectively comparing accounting and finance major wages within the same industry-year, as a more general approach to address omitted variable concerns. Across all specifications, we arrive at the same inference: as technological investment grows, finance major wages rise while accounting major wages weakly decline.

In aggregate, as discussed above, technological advances are likely to have both labor-saving (negative) and labor-augmenting (positive) effects on accounting jobs. To provide further insights into the effects of technology, we focus on two cross-sectional cuts where KPSS predict heterogeneity in labor-augmenting effects, even if our evidence so far suggests that the negative effects dominate. First, positive labor-augmenting effects are less likely for older workers who are most skilled in the earlier technologies and therefore relatively poorly positioned, on average, to adapt to new technologies. Consistent with this, we find that the oldest quartile of workers in all three majors experience, at best, no wage growth with software investment. For accounting majors specifically, wages for the oldest quartile of workers significantly *decline* as software investment expands. Second, labor-augmenting effects are more likely to accrue to workers with relevant training, e.g., specifically in technology or adjacent fields. Focusing on accounting majors with versus without technology-related minors, our evidence suggests that accounting majors with a technology minor see wage *increases* with software spending. Evidence from these two sets of tests highlight the importance of labor-augmenting effects of technology in determining how technological advances affect returns to accounting education.

Our final tests connect our evidence of lagging accounting wage growth to the accounting major declines shown in Figure 1. We study major choices as a function of recent wages earned by accounting and finance majors in the state. We find that as the gap between accounting and finance major wages expands, fewer students in subsequent years choose an accounting major and more choose a finance major.

We make two contributions. First, our evidence directly speaks to current discussions about declining accounting enrollments, and the consequences for the accounting labor market and accounting work. There are multiple proposals by the AICPA and other constituents to alleviate supply-side constraints in hopes of reversing the enrollment decline.[2] Our evidence presents a different perspective that we hope informs the discussion. As a starting point, we show that relative wages for accounting majors have significantly fallen. This finding is difficult to square with a straightforward supply shortage interpretation, and raises doubts that supply-focused reforms alone (e.g., restructuring or abandoning the 150-hour rule) can fully reverse the enrollment decline. Then, we illustrate how sectoral technological investment is associated with less employment and wage growth for accountants than other business majors—a finding in line with automation reducing the returns to accounting education.

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[2] For example, see the AICPA's Pipeline Acceleration Plan (https://www.aicpa-cima.com/resources/article/draft-plan-to-accelerate-talent-pipeline-solutions), which features initiatives related to career perceptions, firm culture and business models, diversity, equity, inclusion, partnering with colleges and universities, training, and education. Notably, none of the "root causes" mentioned in the Plan relate directly to technological advances or adoption.

An implication of our evidence is that enrollment declines are more likely to reverse if accounting education is reformed to increase the odds that students benefit from labor-augmenting effects of technology, rather than being subject to displacement from labor-saving effects.[3] Overall, although we do not seek to rule out supply-driven factors contributing to recent accounting enrollment declines (e.g., exam-related barriers to entry or changes in the nonpecuniary benefits of an accounting career), our evidence suggests that demand-side factors are crucial to consider, especially as technological advances continue.

Second, our paper adds to the nascent literature on how technology is transforming the accounting profession. Existing work in this area focuses on artificial intelligence tools at audit firms (Law and Shen 2020), auditor skill demands as a function of their technological investments (Ham et al. 2022), and technological tools that can substitute for financial statements in the lending process (Minnis, Sutherland, and Vetter 2023). We contribute by providing evidence that declining labor-market returns to accounting education, important in and of themselves, can help explain declining enrollments in accounting programs. Our findings align with recent theoretical developments in labor economics elucidating both labor-saving and labor-augmenting effects of technologies, which vary depending on workers' tasks and training (Goldin and Katz 2009; Acemoglu and Restrepo 2018; Kogan et al. 2023).

2 Theoretical Framework: Linking technological change to accounting enrollments

Our theoretical framework draws on two streams of literature in labor economics. The first shows how educational choices are influenced by returns to human capital. The second links technological advances to employment and pay.

[3] See also Kachelmeier (2002) and Howieson (2003) for discussions of accounting education reform in the face of declining enrollments and the evolving work environment for accountants through the 1990s.

Higher expected payments for specific types of human capital naturally increase incentives to acquire these types, e.g., via educational investments (Roy 1951; Deming and Noray 2020).[4] Furthermore, we can view jobs and, by extension, career paths as differentiated through the types of human capital needed to succeed (Deming and Khan 2018). As such, changes in pecuniary returns to accounting careers lead to changes in incentives for individuals to acquire accounting-related human capital, and thus, affect accounting enrollments. Of course, what matters is not only absolute returns to human capital acquisition, but also returns relative to plausible alternative career paths, such as those with substantial skill overlaps like finance or other business fields.

In terms of technological advances, wages for accountants are naturally a function of the supply and demand for accounting labor. While supply is determined by accounting graduations and post-educational career entry and exit, demand is a function of the productivity of accounting labor.[5] Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018; AR) show how novel technologies that expand the degree to which capital (e.g., information technology investments) can substitute for labor affect labor demand. There is a direct effect involving the displacement of labor that replaces humans in automated tasks (AR). However overall labor demand may not decline, as technology can also create new higher-productivity tasks, which AR label as a reinstatement effect. AR's reinstatement effect depends on the economy's ability to create new tasks in which the displaced workers' labor is valued. If the new tasks require substantially different skills and/or training, then we can expect to observe a net decrease in the returns to the displaced human capital.

[4] These theories should be interpreted only as implying that financial payoffs influence educational investments such as the choice of undergraduate major. They do not imply the exclusion of other determinants, such as prestige or work-life-balance preferences.

[5] Besides productivity, additional factors such as the industrial organization of employers or accounting standards can also affect employee demand and wages. Aobdia et al. (2020) provide evidence that local CPA firm concentration can be associated with demand for auditors. Le (2024) shows that accounting demand shifts from creative to compliance-related tasks as GAAP restrictiveness increases.

KPSS, in related work, show how the labor-saving effects of technology can lead to displacement, wage declines, and job losses; while labor-augmenting effects can be associated with reinstatement, higher wages, and greater employment levels. Technology is labor-saving when it can provide a reasonable substitute for work previously done by a person. Their labor is saved, which lowers demand for that labor. Technology is labor-augmenting when it improves workers' productivity without replacing them. Higher productivity implies a higher value of a worker's output, which increases demand for their labor, boosting wages and job opportunities.

Focusing on the implications for accounting, the direct and labor-saving effects are likely to reduce returns to accounting jobs, particularly those at the lower end of the human capital spectrum (e.g., bookkeeping, account analysts, and entry-level CPAs). Simple tax returns, for instance, can now largely be completed by software, and the software that completes the simplest tax returns is available for free. Tax return preparers displaced by software may find it difficult to put their training to use in other settings, limiting the positive reinstatement effects. By contrast, accountants offering business insights can benefit from labor-augmenting technology that, for instance, allows them to more efficiently analyze data, access information, and track customers.

However, whether these labor-augmenting technologies translate into greater accounting enrollments depends on the relative degree to which accounting versus other majors' labor is augmented. Overall, while the labor-saving and displacement effects of technology are expected to reduce accounting majors, the effects of labor-augmenting technologies should depend on whether the degree of augmentation is higher for accounting or other majors in potential accountants' choice sets (e.g., finance or other business fields).

3 Data and summary statistics

3.1 Data

We examine how accounting major employment and wages relate to technological investment by firms using two public data sources. First, the American Community Survey (ACS) of the U.S. Census provides the wages, occupation, college major, industry, location, and biographical data for a sample of surveyed individuals. The college major field is only populated starting in 2009, so our sample spans 2009-2019. Majors are reported in Question 12 of the ACS.[6]

Second, the Bureau of Economic Analysis (BEA) records private nonresidential fixed investment at the industry-year level. Specifically, we proxy for industry technology adoption by using the software asset categories. There are three individual categories (prepackaged software, custom software, and own-account software) plus an all software figure that aggregates investment across the three categories. The BEA provides the following definitions (Soloveichik and Wasshausen 2013): prepackaged software is that which is "sold or licensed in standardized form. It typically requires little or no modification for use and includes both systems software and applications software" (p. 17). Custom software is "tailored to the specifications of a business enterprise or government unit. It may include new computer programs as well as programs incorporating preexisting or standardized modules" (p. 19). Own-account software "consists of in-house expenditures for new or significantly-enhanced software created by business enterprises or government units for their own use… Because there are no market transactions for own-account software, nominal investment is estimated by summing the costs of production, which include employee compensation–both wage and nonwage–and the costs of intermediate inputs" (p. 21-22).

[6] The most common business major categories include "accounting", "business economics", "finance", "international business", "marketing and marketing research", "operations, logistics, and e-commerce". There is no "Data Analytics" category. Some individuals may provide multiple responses (e.g., if they have a major and a minor, or a double major). Following the ACS survey manual, we take the first response that the participant provides as their major.

Our assumption is that software investment is a good proxy for firms' technological resources and capabilities that enable automation and new task creation (Jones and Tonetti 2020; Charoenwong et al. 2023), that in turn affect labor demand.[7] Supporting this, KPMG's most recent balance sheet shows that the largest asset category is software; software is also a major asset category for many non-public accounting firms.

The combined dataset offers several key advantages for our purposes. The Census data are randomly drawn from the U.S. population, and therefore sidestep selection issues with alternative data sourced from, for example, professional networking websites and online job postings. The Census wage data are based on actual earnings, rather than compensation or compensation ranges advertised in job postings which may not materialize. And finally, the Census collects college major information.

3.2 Summary statistics

Table 1 presents summary statistics, with Panel A (B) reporting figures for individual- (industry-) level observations. For our sample of individuals with an undergraduate business degree, 23% have an accounting major, 9% have a finance major, and the remaining 68% have some other business major (e.g., marketing, operations, or organizational behavior). Forty-five percent of our sample is female, 7% is Black, 9% is Asian, and 7% is Hispanic. The average age is 44, and the average (median) wage is $86,104 ($62,000) (wage figures are rounded to the nearest thousand in the raw data).

Panel B reports that for the average industry-year in our sample, there are 208 accounting majors, 85 finance majors, and 622 other business majors. Aggregate prepackaged, own, custom,

[7] Our analysis of software *investment* rather than the software *stock* follows the empirical labor and productivity literatures. The BEA data records flows, not stocks. Aggregating flows into stocks requires auxiliary assumptions (e.g., about depreciation rates). Focusing on flows is equivalent to assuming a fast depreciation rate, which is descriptive for software and other technological investments (Solow 1956; Hall and Jones 1999).

and total software investment in an average industry-year is \$1,981, \$2,033, \$899, and \$4,914 million, respectively. (Note that because the Census and BEA draw random samples, these employment and investment figures understate the population totals).

4 Technology adoption and returns to accounting human capital

4.1 Employment

Our employment tests use the following empirical specification:

$$y_{jmt} = Software_{jt} + Accounting_m x\ Software_{jt} + Finance_m x\ Software_{jt} + \alpha_{jm} + \alpha_t + \varepsilon_{jmt}. \quad (1)$$

The unit of observation is industry-major-year, where *j* indexes industries (three-digit NAICS), *m* indexes college majors, and *t* indexes years. Our sample is limited to individuals with an undergraduate business degree. The dependent variable is *Log Employment*, the log number of workers in the industry-major that year. $Software_{jt}$ measures the log dollars of investment at the industry-year level, measured across the four categories described earlier. We group individuals into three categories based on their major: *Accounting*, *Finance*, and all remaining programs (which we use as the holdout category in our regression). We control for industry-major fixed effects (α_{jm}) to account for typical employment for a college major-industry combination, and year fixed effects (α_t) to account for the overall state of the economy and labor market. The year fixed effects also help control for the overall enthusiasm for accounting and work-life-balance preferences. We cluster standard errors by industry-major.

Table 2 presents the results. In column 1, we find that business major employment significantly increases with prepackaged software investment. The 16.1% coefficient on *Software* implies that doubling the industry investment in prepackaged software is associated with a 16.1% increase in business major jobs in the industry. Perhaps a more suitable calibration utilizes the typical year-over-year growth in prepackaged software investment of 11%. Using this as a benchmark, the coefficient implies a 1.8% increase in business major employment.

Of course, our focus is on accounting and finance major employment. Column 1 shows a -8.9% coefficient for *Accounting* x *Software*, indicating that accounting major employment grows far less with technological investment.[8] By contrast, the *Finance* x *Software* interaction is a significantly positive 6.0%, indicating even faster employment growth with technological investment for finance majors than other business majors. The remaining Table 2 columns study the other software investment categories and find a similar pattern: software investment significantly expands finance major employment, while producing some additional jobs for other business majors and the fewest jobs for accounting majors.

4.2 Wages

Our wage tests employ the following empirical specification:

$$y_{ijmt} = Software_{jt} + Accounting_{im} x\, Software_{jt} + Finance_{im} x\, Software_{jt} + \alpha_{jm} + \alpha_{am} + \alpha_t + X_{ijmt} + \varepsilon_{ijmt}. \tag{2}$$

The unit of observation is individual-industry-major-year, where *i* indexes individuals, *a* indexes age quartiles, *j* indexes industries (three-digit NAICS), *m* indexes college majors, and *t* indexes years. Once again our sample is limited to those with an undergraduate business degree, and we use the same major (accounting, finance, and the remaining majors), and Software (prepackaged, custom, own account, and all) categories as before. The dependent variable is *Log Wages*, the log of the individual's wages that year based on the Census INCWAGES variable. This variable includes wages, salaries, commissions, cash bonuses, tips, and other money income.

We control for industry-major fixed effects (α_{jm}) to account for typical wages for a college major-industry combination, and age quartile-major fixed effects (α_{am}) to account for curricular

[8] The sum of the main effect on *Software* and the Accounting x *Software* interaction term is positive and significantly different from zero, indicating overall labor growth. However, accounting major choices relate to relative benefits from different career paths, implying that the relevant coefficient for linking labor market outcomes to college major choice is the interaction term, rather than the sum of the main effect and interaction term.

changes within programs over time. We also include year fixed effects (α_t) to account for the overall state of the economy and labor market. Our vector of controls X include indicators for the Census gender and race categories, employment status, and age. We cluster standard errors by industry-major. Intuitively, our specification examines how wages for accounting and finance majors respond to sectoral investment in technology, using other business major wages as a control.

Table 3 presents the results. In column 1, there is a positive but insignificant coefficient for *Software*, indicating weak wage growth for business majors when firms in their sector expand their prepackaged software investments. Interestingly, the pattern is quite different for finance and accounting majors. As prepackaged software investment grows, finance major wages significantly expand above the rate for other business majors, but accounting major wages (weakly) lag behind this baseline rate. We find that the same pattern emerges for other types of software investment in columns 2-4: as software investment expands, finance major wages grow significantly above the rate for other business majors, while accounting major wages are relatively stagnant.

We then conduct a series of robustness tests with the aim of strengthening our inference that the wage patterns we document are explained by technology adoption. For simplicity we focus on the *Total* software investment variable, but our inferences are the same using the other software variables.

First, while we infer from the similar employment (Table 2) and wage (Table 3) patterns that demand-side factors are at play, our tests to this point do not directly rule out one particular oft-mentioned supply-side factor: CPA licensing requirements. These requirements encompass the 150-hour rule, which increased the educational requirements for those sitting for the CPA exam, as well as dues, continuing education requirements, and reciprocity rules. Such requirements are linked to reduced entry to the profession (Barrios 2022; Sutherland, Uckert, and Vetter 2024), which can independently affect wages. Column 1 of Table 4 adds a state x year fixed effect to equation (2), such that we compare wages for individuals subject to the same set of licensing requirements but working in industries with different software investment levels. We find a similar pattern that shown in Table 3: finance wages significantly rise with software investment, while accounting wages weakly decline. Moreover, we note that by 2009, the beginning of our sample, all but six states had adopted the 150-hour rule, making it unlikely that rule adoption could have a meaningful effect on our results.

Column 2 then addresses an omitted variable bias concern. Specifically, our software investment variables may simply be picking up latent economic growth—when the sector is booming, firms may increase investment in all asset types. Then, if accounting major wages tend to respond less than finance major wages to such growth, it could explain our Table 3 findings. To address this, we introduce controls and interactions for equipment investment (*Equipment*), the largest investment category in the BEA data, to account for overall investment behavior. We find that once again, the *Finance* x *Software* interaction is significantly positive, while the *Accounting* x *Software* interaction is weakly negative. Moreover, the *Accounting* and *Finance* interactions for equipment are of the wrong sign to support a latent growth interpretation of our Table 3 results.

Last, column 3 addresses omitted variable concerns using a more flexible approach. We limit the sample to accounting and finance majors and introduce an industry x year fixed effect. In this specification, we are comparing wage changes for accounting and finance majors in the same industry-year, which reduces concerns about, for example, unobservable economic conditions or sector-level outsourcing opportunities driving our results. We arrive at a similar inference: the *Accounting* x *Software* interaction is significantly negative, indicating that technology adoption increases finance major wages more than accounting major wages.

4.3 Cross-sectional evidence on worker characteristics

Next, we study how the wage-software investment response depends on worker age. Specifically, we assign individuals to age quartiles within the major-year, and introduce interaction terms for the oldest workers (*Age Quartile 4)*. We add an age quartile dimension to the industry-major fixed effect, such that we control for typical wages for each worker age category within an industry-major. We also control for major x year fixed effects, which account for nationwide wage trends for each major.

Table 5 presents the results. Column 1 shows that the interactions between each major type and software investment essentially echo our Table 2 findings: of all majors, finance majors experience the greatest wage growth with technological investment. In terms of age, the oldest workers see at best no wage growth, and in some cases, negative wage growth, as prepackaged software spending increases. This pattern emerges for all three major categories: the triple interaction coefficient for *Age Quartile 4* and prepackaged software investment for each major type is significantly negative, indicating that the wage gains we document earlier are limited to younger workers. Columns 2-4 report similar evidence for our other software variables.

Table 6 studies how accounting major wage changes depend on whether the individual has a minor in a technology-related field.[9] To do so, we estimate a modified version of equation (2), where the sample is limited to accounting majors and we introduce an interaction between our software investment variables and *Tech Minor*, an indicator for individuals with a technology-related minor. Specifically, we examine the ACS minor degree field and classify individuals whose minor is "computer and information sciences," "mathematics and statistics," "engineering," or

[9] There are too few accounting majors with technology minors to study employment counts, as we do in Table 1. Hence, we limit our analysis of technology minors to wages.

"engineering technology" as technology minors. Approximately 2% of accounting majors in our sample have a technology minor.

Column 1 shows that while accounting wages weakly fall with prepackaged software investment, those with a technology-related minor see wages significantly increase. The 14.8% coefficient on *Tech Minor* x *Software* implies that a typical year-over-year increase in prepackaged software investment is associated with a 1.5% wage increase for individuals with an accounting major and a technology minor. Columns 2-4 study the other software categories and find a similar pattern: having a technology-related minor leads to *higher* wages with more software spending.

5 Relative wages and major choices

Our final analyses seek to link accounting-finance major wage differentials to major choices. As a descriptive first step, Figure 1 plots the share of graduating business majors that are accounting and finance majors, from 1990 to 2021. The blue series shows a general increase in finance majors over the period, with the share peaking at 16% in 2021. By contrast, the red series shows an accounting major decline that is particularly stark in the late 1990s and last three years of our sample. The accounting major share of business graduates is 22% in 1990 and falls to 14% in 2021. Then, the green series plots the wage difference between the median earner with an accounting major and the median earner with a finance major. In 2009, the earliest year our data permits us to measure the wage difference, accounting majors made approximately $5,000 less than finance majors. In subsequent years, as the wage difference grows, the share of accounting majors declines and the share of finance majors climbs. In 2021, the wage difference reaches $17,000 and the finance major share surpasses the accounting major share for the first time in our sample.

To more formally study the major choice-wage relation, we model the difference between the (log) number of accounting and finance majors in a state-year as a function of the difference between (log) wages for accounting and finance majors in that state in recent years (the lags vary as labeled in the table). For majors, we identify individuals residing in a given state, and infer major choice years by assuming that individuals chose majors at age 20 following prior literature (Leighton and Speer 2020; Blom, Cadena, and Keys 2021).[10] For wages, we measure mean wages (Panel A) and wages at various percentiles (Panel B) for accounting and finance majors within the state-year. Intuitively, lagging the wage difference allows us to see how students' major choices respond to the wages they observe in the local economy.

In Panel A, we find a positive and generally significant coefficient on the wage gap variable: similar to Figure 1, as the gap between accounting and finance major wages grows, students become less likely to choose an accounting major and more likely to choose a finance major. Panel B then examines the major choice based on different parts of the wage distribution. Entry-level jobs tend to have the lowest wages for a given major, whereas the highest wages are earned by individuals later in their career (e.g., a partner at a CPA firm or investment firm). Our results indicate that wages for most parts of the wage distribution are important to major choices, consistent with individuals considering the lifetime earnings of a career path when deciding on a major. Columns 1-4 find a positive and significant coefficient for *Wage Difference*, and column 5 finds a positive but insignificant coefficient, possibly due to top-coding in the wage data.[11] Overall, our takeaway from Table 7 is that when choosing a major, individuals consider both the entry-level and long-run wages for workers with a given major, as observed in the local labor market.

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[10] Take, for example, an individual in the 2020 Census survey wave of the American Community Survey. At the time of the survey in 2020, the individual is 30 years old, resides in state A, and majored in accounting. That individual is assumed to have chosen an accounting major in state A in 2010 (at age 20).

[11] To preserve the anonymity of survey participants, the census does not provide the actual wages of individuals earning above a given amount (e.g., $200,000) or percentile (99.5th percentile in the state). This data feature is particularly salient for accounting and finance occupations, where top salaries tend to be high in absolute terms and compared to most other occupations.

6 Conclusion

Recent years have seen a stark decline in the share of business school undergraduates majoring in accounting. Our results suggest that the decline is, at least in part, a rational response by students facing lower wages in accounting careers relative to other plausible educational paths. But the implications are subtle. Although many have called for higher wages or supply-focused reforms in order to reverse the enrollment decline, our analyses suggest that such responses may not address important underlying economic forces driving the decline. Specifically, technological advances have created new tools that can substitute for accounting labor, thus reducing the willingness of employers to pay competitive wages for accounting majors entering the workforce.

There are few signs of these types of technological advances, or employers' willingness to embrace them, reversing or even slowing. As such, accounting majors may continue to decline, absent significant changes in education that shift technology's effects on accounting jobs from labor-saving to labor-augmenting. In this respect, our results relate to recent efforts by colleges to reform curricula to prepare accounting graduates to benefit from ongoing and inevitable technological advances.

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Figure 1: Graduate Shares and Pay for Accounting and Finance Majors

This figure plots graduate shares and pay for accounting and finance majors. The left axis measures the percent of graduating business majors that are accounting and finance majors, from 1990-2021, based on Census data. The right axis measures the wage difference between the median earner with an accounting major and the median earner with a finance major, from 2009-2021.

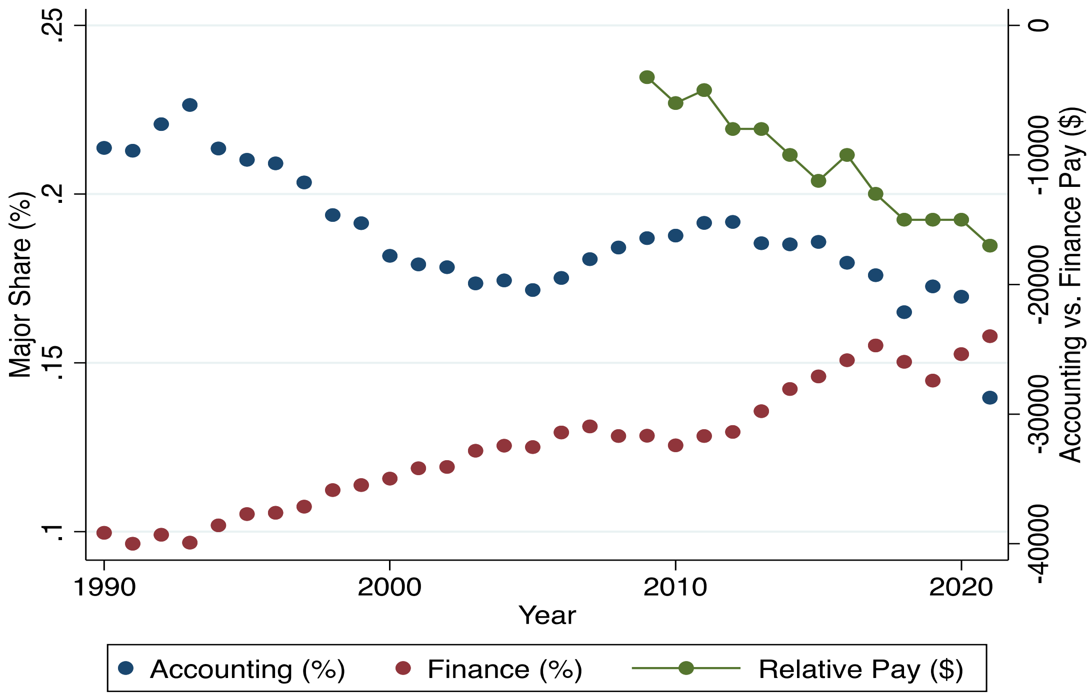

Table 1: Summary Statistics

This table provides summary statistics for the variables used in our analyses. The sample spans 2009-2019, and the sample is limited to individuals with an undergraduate business degree. Panel A reports individual-level figures, while Panel B reports industry-level figures.

Panel A: Individual-level

	Mean	Std Dev	P25	P50	P75	N
Accounting	0.23	0.42	0.00	0.00	0.00	662,815
Finance	0.09	0.29	0.00	0.00	0.00	662,815
Female	0.45	0.50	0.00	0.00	1.00	662,815
Black	0.07	0.26	0.00	0.00	0.00	662,815
Asian	0.09	0.29	0.00	0.00	0.00	662,815
Hispanic	0.07	0.26	0.00	0.00	0.00	662,815
Age	44.34	12.86	34.00	44.00	54.00	662,815
Wage	86,104.55	89,786.09	35,000.00	62,000.00	100,000.00	662,815

Panel B: Industry-level

	Mean	Std Dev	P25	P50	P75	N
# Accounting	208	533	32	64	182	732
# Finance	85	156	12	27	69	732
# Business Major	622	951	110	242	731	732
Prepacked Software	1,981	3,985	222	519	1,581	732
Own Software	2,033	4,881	67	173	754	732
Custom Software	899	2,683	20	90	367	732
All Software	4,914	10,652	328	790	2,666	732

Table 2: Employment by Major and Software Investment

This table studies employment by major and software investment using equation (1). The unit of observation is industry-major-year. The dependent variable is *Log Employment*, the log number of workers recorded by the Census. The three college major categories are Accounting, Finance, and a control group of all other undergraduate business majors. The *Software* categories measure log dollar investments that industry-year in the software type as labelled at the bottom of the table. At the bottom of the table, we also report the p-value for a test of whether the sum of the software coefficient and its interaction with the *Accounting* indicator is different from zero. The sample is limited to undergraduate business majors. Standard errors are clustered at the industry-major level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	Log(Employment)			
	(1)	(2)	(3)	(4)
	Prepackaged	Own	Custom	All
Accounting x Software	-0.089***	-0.064*	-0.037	-0.085**
	(0.032)	(0.038)	(0.034)	(0.035)
Finance x Software	0.060*	0.034	0.018	0.056
	(0.035)	(0.046)	(0.043)	(0.040)
Software	0.161***	0.171***	0.149***	0.166***
	(0.022)	(0.023)	(0.020)	(0.023)
Sum of coefficients	0.072	0.107	0.112	0.081
P-value sum of coefficients	0.028	0.002	0.000	0.015
Industry x Major FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,966	4,966	4,377	4,966
Adjusted R-squared	0.975	0.975	0.976	0.975

Table 3: Wages by Major and Software Investment

This table studies wages and software investment using equation (2). The unit of observation is individual-industry-major-year. The dependent variable is *Log Wages*, the log of wages recorded by the Census. The three college major categories are Accounting, Finance, and a control group of all other undergraduate business majors. The *Software* categories measure log dollar investments that industry-year in the software type as labelled at the bottom of the table. At the bottom of the table, we also report the p-value for a test of whether the sum of the software coefficient and its interaction with the *Accounting* indicator is different from zero. The sample is limited to undergraduate business majors. Standard errors are clustered at the industry-major level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	Log(Wage)			
	(1)	(2)	(3)	(4)
	Prepackaged	Own	Custom	All
Accounting x Software	-0.005	-0.014	-0.016	-0.008
	(0.012)	(0.018)	(0.017)	(0.015)
Finance x Software	0.043**	0.055*	0.044	0.052**
	(0.022)	(0.032)	(0.033)	(0.025)
Software	0.011	0.011	0.006	0.008
	(0.010)	(0.012)	(0.009)	(0.011)
Sum of coefficients	0.006	-0.003	-0.010	0.000
P-value sum of coefficients	0.544	0.865	0.441	0.969
Industry x Major FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Observations	662,815	662,815	628,235	662,815
Adjusted R-squared	0.285	0.285	0.274	0.285

Table 4: Wages by Major and Software Investment—Robustness

This table studies wages and software investment using variations of equation (2). The unit of observation is individual-industry-major-year. The dependent variable is *Log Wages*, the log of wages recorded by the Census. The three college major categories are Accounting, Finance, and a control group of all other undergraduate business majors. The *Software* categories measure log dollar investments that industry-year across all software types (i.e., the *Total* category in prior tables). *Equipment* measures the log dollar investments in equipment that industry-year. At the bottom of the table, we also report the p-value for a test of whether the sum of the software coefficient and its interaction with the *Accounting* indicator is different from zero, if applicable. The sample is limited to undergraduate business majors, except in column 3 where the sample is limited to accounting and finance majors. Standard errors are clustered at the industry-major level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	Log(Wage)		
	(1)	(2)	(3)
Accounting x Software	-0.018	-0.028	-0.050***
	(0.016)	(0.019)	(0.018)
Finance x Software	0.085***	0.099***	
	(0.023)	(0.020)	
Software	0.006	0.040**	
	(0.011)	(0.016)	
Accounting x Equipment		0.014	
		(0.025)	
Finance x Equipment		-0.031	
		(0.036)	
Equipment		-0.044**	
		(0.018)	
P-value sum of coefficients	0.474	0.474	-
Industry x Major FE	Yes	Yes	Yes
Age x Major FE	Yes	Yes	Yes
State x Year FE	Yes	No	No
Industry x Year FE	No	No	Yes
Individual Controls	Yes	Yes	Yes
Observations	662,815	662,815	211,075
Adjusted R-squared	0.226	0.251	0.243

Table 5: Wages by Major and Age, and Software Investment

This table studies wages and software investment using a variation of equation (2). The unit of observation is individual-industry-age quartile-major-year. The dependent variable is *Log Wages*, the log of wages recorded by the Census. The three college major categories are Accounting, Finance, and a control group of all other undergraduate business majors. The *Software* categories measure log dollar investments that industry-year in the software type as labelled at the bottom of the table. *Age Quartile 4* is an indicator for individuals in the oldest age quartile, assigned within major-year. The sample is limited to undergraduate business majors. Standard errors are clustered at the industry-major level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	Log(Wage)			
	(1)	(2)	(3)	(4)
	Prepackaged	Own	Custom	All
Age Quartile 4 x Software x Accounting	-0.086***	-0.083**	-0.067**	-0.084***
	(0.032)	(0.032)	(0.031)	(0.032)
Software x Accounting	0.016	0.010	0.004	0.012
	(0.016)	(0.017)	(0.015)	(0.017)
Age Quartile 4 x Software x Finance	-0.082*	-0.081*	-0.073	-0.087**
	(0.044)	(0.045)	(0.048)	(0.044)
Software x Finance	0.064**	0.063*	0.036	0.071**
	(0.031)	(0.034)	(0.027)	(0.030)
Age Quartile 4 x Software x Business	-0.049*	-0.048*	-0.036	-0.048*
	(0.025)	(0.025)	(0.025)	(0.025)
Software x Business	0.030*	0.029	0.015	0.028
	(0.018)	(0.019)	(0.014)	(0.018)
Industry x Major x Age FE	Yes	Yes	Yes	Yes
Year x Major FE	Yes	Yes	Yes	Yes
Observations	626,615	626,615	594,925	626,615
Adjusted R-squared	0.106	0.106	0.092	0.106

Table 6: Accounting Major Wages, College Minors, and Software Investment

This table studies wages, college minors, and software investment using a variation of equation (2). The unit of observation is individual-industry-minor-year. The dependent variable is *Log Wages*, the log of wages recorded by the Census. *Tech Minor* is an indicator variable for accounting majors with a technology minor. The *Software* categories measure log dollar investments that industry-year in the software type as labelled at the bottom of the table. At the bottom of the table, we also report the p-value for a test of whether the sum of the software coefficient and its interaction with the *Tech Minor* indicator is different from zero. The sample is limited to accounting majors. Standard errors are clustered at the industry level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	Log(Wage)			
	(1)	(2)	(3)	(4)
	Prepackaged	Own	Custom	All
Tech Minor x Software	0.148***	0.242***	0.271***	0.202***
	(0.051)	(0.077)	(0.074)	(0.071)
Software	-0.011	-0.016	-0.011	-0.016
	(0.016)	(0.018)	(0.014)	(0.017)
Sum of coefficients	0.137	0.226	0.260	0.186
P-value sum of coefficients	0.009	0.004	0.001	0.010
Industry x Major FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	149,253	149,253	143,394	149,253
Adjusted R-squared	0.269	0.269	0.259	0.269

Table 7: Major Choices and Pay for Accounting and Finance Majors

This table studies major choices as a function of recent pay for accounting and finance majors. The unit of observation is state-year. The dependent variable *Major Difference*, is the natural logarithm of the number of accounting majors minus the natural logarithm of the number of finance majors. *Wage Difference* is the natural logarithm of the mean wages paid to accounting majors minus the natural logarithm of the mean wages paid to finance majors. Columns 1 to 5 extend the time lag for the wage measure as labeled. I.e., column 1 models major choice as a function of relative wages paid in *t-1*, column 2 in *t-2*, etc., as indicated in the row "Lag." In Panel B, we measure the wage differences at various wage percentiles. I.e., column 1 defines the *Wage Difference* with respect to the 10^{th} percentile accounting and finance major wage, column 2 with respect to the 25^{th} percentile wage, etc., as indicated in the row "Wage PCT." All wage percentile differences in Panel B are lagged by three years (*t-3)* relative to the major choice year (*t*). The sample is limited to accounting and finance majors. Standard errors are clustered at the state level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Dynamic Analysis

	Major Difference				
	(1)	(2)	(3)	(4)	(5)
Wage Difference	0.194	0.369**	0.525***	0.167	0.008
	(0.151)	(0.168)	(0.143)	(0.221)	(0.158)
Lag	1	2	3	4	5
Age	All	All	All	All	All
No. of Obs.	532	481	431	382	332
Adjusted R-Squared	0.002	0.010	0.029	0.001	0.001

Panel B: Wage Distribution Analysis

	Major Difference				
	(1)	(2)	(3)	(4)	(5)
Wage Difference	0.105**	0.451***	0.522***	0.475**	0.024
	(0.044)	(0.150)	(0.164)	(0.208)	(0.108)
Wage PCT	P10	P25	P50	P75	P90
Lag	3	3	3	3	3
Age	All	All	All	All	All
No. of Obs.	431	431	431	431	431
Adjusted R-Squared	0.012	0.028	0.019	0.018	0.001