The Market for Accountants

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Abstract

Given the essential role accountants play in the economy, the dynamics of accountant supply and demand have significant consequences for businesses, their stakeholders, and the functioning of capital markets. This paper analyzes the employment patterns, career trajectories, and earnings of college graduates in business fields to understand these dynamics while overcoming empirical challenges: unobservable factors, sectoral movements, and equilibrium outcomes. Utilizing a large dataset of resume information, we specify and estimate a dynamic labor market equilibrium model that jointly characterizes (i) individuals' choices among six sectors: Big 4, Non-Big 4, Internal Accountants, Finance & Consulting, Technology, and Others, considering current and future wage and non-wage attributes; and (ii) employers' within- and across-sector oligopsonistic competition for labor. Our estimates uncover the magnitude of entry barriers, switching costs, wage markdowns, and marginal product of labor across sectors, which are essential hidden factors influencing accountants' career choices. Our counterfactual analysis suggests a competitive labor market increases the labor market share of external accounting despite reducing that of internal accounting.

Keywords: Accountant, Job Mobility, Wage, Non-wage Benefit, Occupation Choice, Dynamic Discrete Choice, Labor Market Equilibrium

JEL Classification Numbers: D63, D83, J16, J62, J64, M12, M21, M41

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1 Introduction

Accountants play an essential role in the capital markets and the broader economy (Ball, 2024). By interpreting and applying accounting principles, they produce information that influences resource allocation, production decisions, and overall welfare (Breuer, 2021; Choi, 2021; Geng et al., 2023; Huber and McClure, 2023; McClure and Zakolyukina, 2024). Given their importance, it is crucial to understand the factors driving the employment of accountants. This issue has received renewed attention recently, as reports indicate a decline in the number of accountants in the economy (Dawkins, 2023; Maurer, 2023).

The employment of accountants is an equilibrium outcome shaped by both supply and demand forces. However, the literature lacks an equilibrium model characterizing how these forces interact to influence labor market outcomes. Such a model also needs to account for the fact that individuals career trajectories are dynamic. As shown in Figure 1, graduates with accounting degrees—and business majors more broadly—frequently begin their careers at accounting firms. However, many of these individuals later transition to other sectors. This dynamic transition highlights the need for a model where individuals make forward-looking career choices across multiple sectors (Bertomeu et al., 2023; Breuer et al., 2024).

This paper estimates a finite-horizon equilibrium model of the labor market for accountants, where employers compete for talent in a multi-sector oligopsonistic labor market and workers make forward-looking dynamic decisions of which sector to work in.[1] We are interested in exploring two broad research questions. First, what economic factors influence workers' career choices between accounting and other jobs (on the supply side) and wage offers (on the demand side)? Specifically, we estimate individuals' returns from employment by one of six mutually exclusive job sectors: Accounting in Big 4 firms, Accounting in Non-Big 4 firms, Internal Accountants in Other Industries, Finance & Consulting, Technology, or Non-Accounting in Other Industries. These returns consist of wages as well as unobservable non-wage benefits and costs, capturing factors such as work-life balance and entry barriers. We also quantify sectoral productivity and potential wage markdowns, which are important determinants of wages. Second, using the estimated parameter values, we

[1] Our framework extends the discrete choice dynamic programming (DCDP) approach (Keane et al., 2011) by incorporating employers' endogenous demand for labor. The DCDP approach builds on dynamic life-cycle frameworks (Keane and Wolpin, 1997; Sauer, 1998; Lee, 2005; Traiberman, 2019) and is a standard tool in labor economics for understanding occupational mobility, career progression, and the effects of counterfactual policy experiments.

analyze the value of accounting education and experience in external accounting jobs as well as the role of non-competitive labor markets in shaping equilibrium accountant employment.

The supply side of our labor market equilibrium model characterizes the occupational choices of individuals who are forward-looking and consider the impact of their occupational choice on their expected future returns. Each period individuals choose one of the six job sectors as defined above. The annual return to an occupational choice depends on wages and non-wage benefits and random shocks that are unobserved by the econometrician. Our model accounts for rich heterogeneity in non-wage factors, including (i) time invariant sector characteristics (e.g., prestige and the extent to which the job has non-monetary benefits like stability, work-life balance, etc.); (ii) structural state dependence (e.g., due to learning about workers' matching value with their sectors); (iii) observed heterogeneity in worker types (e.g., whether the individual holds an accounting or a master degree); (iv) unobserved time-invariant heterogeneity in worker types; and (v) partner promotion in external accounting firms and potential forced turnover (i.e., up or out).

The demand side of our model characterizes how employers in each sector maximize profits by choosing wage offers to attract talent in an oligopsonistic labor market. Equilibrium wages depend on two broad factors. Workers' wages increase with their marginal product of labor. Marginal product of labor might differ across sectors for two reasons. Marginal product of labor varies with the characteristics of workers, and different sectors may hire different workers. Sectors might also inherently differ. For example, technological progress or offshoring may lead to productivity differences (Goos et al., 2014; Deming and Noray, 2020).

Wages decrease with the degree of wage markdowns. In an oligopsonistic market, hiring more workers not only increases the labor cost for the marginal worker but also increases wages for all workers, due to an upward-sloping labor supply curve. As firms internalize the latter impact, equilibrium wage offers are below the marginal product of labor (Lee and Wolpin, 2006; Berger et al., 2022; Yeh et al., 2022). The magnitudes of wage markdowns depend on within- and across-sector competition for talent. In our setting, the labor market of external accounting firms is concentrated with four large accounting firms dominating since 2002. A high concentration increases labor market power, depressing wages (Aobdia et al., 2024). However, the degree of concentration, as measured by the Herfindahl-Hirschman index, is comparable to that of other occupations including finance jobs (Azar et al., 2022). Competition for labor between accounting and other (e.g., finance) sectors increases wages.

We estimate the model using a large dataset of resumes of business graduates, including those in accounting, from Revelio and wage data from CPS (2014–2022). Estimating the model with the maximum likelihood method reveals three key insights into labor supply. First, employees without an accounting degree face a non-monetary cost equivalent to about $18k, if they choose to work for external accounting. This cost could reflect an entry barrier (e.g., the 150-hour rule) or a distaste for accounting jobs due to the restrictiveness of the tasks (Le, 2025).

Second, dynamic incentives are important for workers' occupational choices, accounting for 98% of the variation in workers' total return based on observed factors. Further, we document dynamic preferences for external accounting jobs over workers' careers. For workers without any prior work experience in external accounting, external accounting jobs offer lower non-wage benefits by about $52k (Big 4) and $24k (non-Big 4) than jobs in other sectors. However, workers with external accounting experience in the prior year obtain higher non-wage benefits from continuing to work in the same sector than working in other sectors, reversing the initial costs. Each additional year of Big 4 and non-Big 4 experience is associated with an incremental non-wage benefits equivalent to about $24k and $22k, respectively. This result is consistent with career life-cycle models in which workers learn about their matching value with their jobs, and the reduced uncertainty increases the value of staying in the same job (Gorry et al., 2019). The result could also capture the costs of switching job sectors, such as job search and moving as well as shadow costs such as geographical and family constraints. In addition, when these workers switch to other sectors, while they obtain higher wages, the non-wage benefits the obtain from they new sector are lower by about $46k.

Third, workers exhibit unobserved heterogeneity influencing their career choices and the value of accounting education. Specifically, our estimation indicates two types of workers, accounting for 75% and 25% of the population, respectively. The non-wage benefits of external accounting jobs perceived by the first type are $71k higher than those perceived by the second type. The latter group obtains slightly lower career value from choosing an accounting major, equivalent to a discounted value of $1.790 million over a 20-year horizon, compared with $1.832 million from choosing other business majors. For the former group, the career value from an accounting major is similar to that of other business majors. In addition, workers with external accounting experience have lower lifetime career value than workers without such experience, but earn higher wages.

On the demand side, the marginal product of labor of Big 4 accounting firms is higher than that of other accounting sectors, but is lower than that of the Finance & Consulting sector, which is the highest. Employers in the Big 4 accounting sector offer wages \$3.1k lower than their marginal product of labor, compared to \$2.7 and \$2.8k for non-Big 4 and internal accounting, respectively. Our model also considers partner promotion, a distinctive feature of external accounting careers. The estimated probability of forced turnover conditional on not making partner over workers' career is equal to 72% and 58% for Big 4 and Non-Big 4 firms, respectively, providing large-sample evidence of the up-or-out promotion policy of the audit industry (Ghosh and Waldman, 2010).

Using the estimated parameters of our structural model, we conduct a counterfactual analysis on the competitive labor market instead of the oligopsonistic labor market. We find that this change for all the sections lead more individuals to choose Big-4 firms. External accounting experiences the largest gain in market share, rising from 4.74% to 9.47%. This shift is driven by the relatively large wage markdowns of Big 4 employers, which are eliminated under the competitive labor market. Despite this sizable gain, the total market share of accounting jobs only increases by 13.82% because internal accounting jobs are less attractive to workers compared to other sectors once wages are set to their competitive levels.

The importance of accounting labor market frictions has received fresh attention in recent years. The literature provides important insights about factors influencing individual decisions to choose accounting as their college majors or enter the accounting labor market, such as academic ability, entry frictions due to the 150-hour rule for CPAs and ethnicity, and the attractiveness of accounting jobs (e.g., Shorrock and Kibler, 1923; Madsen, 2015; Bloomfield et al., 2017; Cascino et al., 2021; Barrios, 2022; Carnes et al., 2023; Sutherland et al., 2024; Le, 2025).[2] Recent studies also start to examine demand factors, such as technological advancement (Friedman et al., 2024), and provide early evidence on the dynamics of accountant labor supply (Frecka et al., 2022; Yang, 2024).[3]

Our paper complements these studies by providing a coherent characterization of the labor market for accountants, offering three contributions to the literature. First, we extend the prior

[2] More broadly, a number of studies also examine the effect of accountant labor supply on financial reporting quality (e.g., Hoopes et al., 2018; Lee et al., 2022; Hann et al., 2024; Sherwood, 2025) and the industrial organization of audit firms (Abramova, 2024).

[3] Frecka et al. (2022), who survey one university's accounting alumni, find that although accounting graduates begin their careers in accounting firms, they typically transition to finance and manufacturing industries within five years. Better salary and opportunities are major considerations. Yang (2024) empirically documents future career benefits associated with working for external accounting firms.

literature by comprehensively documenting the key features of accounting labor markets and how these features evolved recently. We analyze the demographics, education, and wage profiles of accountants along with the industrial and organizational structure of accounting industries. Most importantly, we connect these accounting-labor-market specific features to our model assumptions (e.g., non-wage benefits and oligopsony power).

Second, the dynamic equilibrium model developed based on those features provides a unified framework for analyzing demand and supply factors affecting business majors' forward-looking career decisions. To the best of our knowledge, we are the first to estimate a multi-sector equilibrium model for the labor market of accountants with dynamic labor supply. On the supply side, our approach demonstrates that dynamic incentives account for 98% of the variation in workers' total return to labor supply. On the demand side, employer compete for talent with other employers from both the same and different sectors, accounting for how workers make dynamic labor decisions.

Estimating the model allows us to uncover otherwise unobservable theoretical constructs shaping the market for accountants with considerable generality. Specifically, we estimate key factors influencing workers' career choices, including human capital accumulation, structural state dependence of job choices, non-wage benefits, and dynamic considerations. We find a nuanced role of external accounting experience. While such an experience increases wages following career switching, it leads to lower non-wage benefits. We also estimate important drivers of labor demand by quantifying differences in productivity and wage markdowns across sectors.

Third, our paper contributes to the literature by estimating how labor market outcomes (e.g., employment) might change in response to changes in the industrial organization of the labor market. We show that these factors play important roles in explaining the equilibrium supply and demand of accountants in the economy.[4] The findings highlight the importance of the industrial organization of the accounting industry for the employment of accountants.

The rest of the paper is organized as follows. Section 2 provides contextual descriptive evidence. Section 3 presents the accounting labor market equilibrium model and motivates its key assumptions. Section 4 discusses the identification and estimation method. Section 5 contains the

[4] We can also point out the theoretical similarities and differences between prior studies and our study. The literature on the labor market for lawyers has several theoretical frameworks. One of them is Sauer (1998), who describes the market for lawyers in terms of job mobility. Sauer (1998) calls for future research that embraces demand factors, promotion policies, and gender differences. As we expand this model to the labor market for accountants, we incorporate these three additional theoretical features into our model.

estimation results and discusses an evaluation of model fit and counterfactual analyses. Section 6 presents conclusions.

2 Descriptive Evidence on the Market for Accountants

In this section, we provide descriptive evidence of key attributes of the accounting labor market in the 21st century to provide context for the structure of our model and the parameters we estimate. These attributes include the declining employment of accountants and enrollment in accounting majors, the concentrated industry structure and high-stakes promotion policy of accounting firms, and the competing wage profiles of neighboring sectors.

2.1 Demographics of Accountants

We begin with an overview of the demographic characteristics of "Accountants and Auditors" using Current Population Survey (CPS) data for the years from 1968 to 2023. The CPS is a monthly survey of 65,000 households conducted by the US Bureau of the Census. It is a large representative public data source that is widely used in labor economics and accounting (Acemoglu and Autor, 2011; Madsen, 2013). These data contain rich information on demographics and employment. Given the focus of our paper, we limit our analysis to accountants and auditors. Within the CPS occupation classification, the category of accountants and auditors is distinct from that of "Bookkeepers and Accounting and Auditing Clerks," who might have different characteristics.[5]

The data in Table 1 indicate that approximately 1% of the workforce currently holds an accounting position. This proportion increased from 0.4% in 1968 to a high of 1.2%, in the 2010s, followed by a sizable decline in the most recent years (e.g., 2013 to 2023). Over the same period, real wages remain stable. There has also been a notable rise in the representation of women within the accounting field, from 24% in 1968 to 59% in 2023. These increases in entries initially corresponded to a decline in the average level of experience among accountants in the economy,

[5] The CPS occupation code for "Accountants and Auditors" is 023. Table 1 starts with 1968 because 1968 is the first year in IPUMS-CPS to use the full set of occupation and industry codes. We use the CPS 3-digit occupation codes (occ1990) for consistency in Table 1. Four occupations are classified as "Financial Records Processing Occupations" (e.g., Cost and Rate Clerks). The employment and wage patterns for this alternative definition of accountants are largely consistent with those shown in Table 1, although educational attainment and wage are lower for "Financial Records Processing Occupations." ACS provides another alternative dataset. We find the same pattern when we use alternative data and when we use sample weight. Refer to https://cps.ipums.org/cps/ and https://usa.ipums.org/usa/.

which then reverted around 1993. The trend also aligns with a persistent and nearly monotonic increase in educational attainment within the profession. Note that by the year 2023, the average educational level for accountants was a college degree (i.e., 16 years), and a meaningful portion of the accounting profession held a master's degree in accounting. This observation shapes our sample selection criteria. Note also that only about 20% of accountants are employed in the accounting service industry. Consequently, an understanding of internal accountants' and auditors' labor market dynamics is critical to understanding the accounting labor market.

We compare these observations with the market for lawyers to further understand the distinctive features of accountants' labor markets. The market for lawyers is a relevant comparison to the market for accountants given its professional nature and high compensation (Rosen, 1992). The high compensation of lawyers is tied to their high educational attainment. The online appendix Table OA1 indicates that the education level and experience are around 18 to 19 years, and the wage of lawyers has recently increased. Lawyers account for a smaller portion of the workforce, representing 0.1% in 1968 and rising to 0.8% in 2023. The proportion of women lawyers increased from 3% in 1968 to 46% in 2023. In contrast to accountants, lawyers are more inclined to remain within the legal service industry rather than transitioning to roles like general counsel in organizations outside law firms (Sauer, 1998).

2.2 Education for Accountants

We turn next to descriptive evidence concerning students majoring in business, including accounting, and their initial job choices. Table 2 shows the descriptive statistics based on data from IPEDS. Post-secondary education is a crucial factor in the supply of accountants. To ensure consistency across a longer time span, we initially analyze the number of bachelor's and master's degrees awarded in accounting by all universities from 1980 to 2020.

We first examine time-series patterns of accounting majors. As observed in the demographic data in Section 2.1, there was a notable influx of accounting majors into the labor force during the 1980s and 1990s. As a result, average experience levels were lower during the same period. The number of degrees awarded started at 46,793 in 1980. This figure remained relatively stable, fluctuating between 45,000 and 55,000, until 1996. Following a dip in 2000, the number of master's degrees in accounting continued to rise until reaching a peak in 2016. Barrios (2022) documents how the increase in educational requirements for CPA certification contributed to this pattern. The peak of accounting graduates occurred in 2016, reaching 70,156. Subsequently, there has been a consistent decline since 2015, sparking discussions about a potential shortage of accountants.[6]

Regarding the career choices of accounting majors, we find that many do not choose to work for accounting service firms according to the IPEDS and AICPA data, which contain hires by accounting service firms. About 50% of accounting graduates find a job in accounting sectors, which implies that the other half find a job in non-accounting sectors.[7] Given this finding, our empirical analysis focuses on workers' choices among accounting job sectors. We differentiate between external accounting, internal accounting, and non-accounting job sectors.

Next, we broaden the sample to include business college and graduate students majoring in business. We focus on these students because resume data collected by Revelio indicate that accounting and business majors account for 70% of accountants working at large accounting companies. In Online Appendix Table OA5, we list the most frequent majors. In terms of schools sending the greatest number of students to accounting firms, multiple universities famous for their Master of Accounting programs (e.g., University of Illinois Urbana-Champaign) feature prominently, as Online Appendix Table OA6 shows.[8] In terms of initial job choices, accounting firms are popular, but a meaningful number of students take their first job in the Finance & Consulting and Technology industries, as Figure 1 shows.

2.3 Industrial and Organizational Structure of Accounting Firms

Considering that many accounting graduates start their careers at accounting firms, we describe the industrial structure of accounting firms. The accounting industry is dominated by a few large accounting firms: Deloitte, E&Y, KPMG, and PwC. This product market concentration is well documented in the literature (GAO, 2003; Eshleman and Lawson, 2017; Abramova, 2024). From 1988 to 2002, the Big 8 became the Big 4 through multiple mergers and the demise of Arthur

[6]Figure OA1 shows the declining proportion of undergraduates choosing accounting as a major. Technical advancements and the repetitiveness of accounting tasks have been proposed as factors contributing to lower enrollments in accounting majors and lower wages for accountants (Baksy, 2023; Friedman et al., 2024). Interestingly, Madsen and Piao (2021) find that accounting jobs are not more miserable than other jobs, where a miserable job is defined as repetitive, rules-bound, sedentary, rigid, and uncreative.

[7]The results are similar when we use the AIPCA dataset. This dataset is based on a 2018 survey of 907 universities with a response rate of 12%. In the US, there were about 160 million employed workers in 2023. Table 1 indicates that 1% represents 1.6 million accountants over about 40 years of their careers (i.e., 40,000 per each experience cohort).

[8]See Online Appendix Table OA6.

Andersen (GAO, 2003). Table 3 documents that from 2010 to 2024, the proportion of revenues generated by Big 4 firms relative to the top 100 accounting firms is 73%. The recent literature emphasizes that this industry concentration results in monopsony power in the input market. Aobdia et al. (2024) document that the labor market power in the audit industry has two opposite effects: lower wages and higher audit quality. Using Burning Glass Technology (BGT) job posting data (Sran, 2021), we estimate that the average Herfindahl-Hirschman Index (HHI) of accountants is slightly less than 5,000 in recent years. This is similar to the HHI of other occupations including finance jobs, although the nationwide HHI may be different. In general, the DOJ defines a high market concentration as an HHI higher than 2,500 at the commuting zone level (Azar et al., 2022). However, we calculate HHI at the county level, which is comparable to half of that at the commuting zone level.[9] The average number of employers for accountants in a county-year is 20. Online Appendix Figure OA2 describes the trends of HHI in the labor market for four occupation categories: accounting, finance, technology, and other jobs.

2.4 Earnings Structure of Accountants

We next examine the wage structure for accountants with a regression analysis using the CPS data in Table 4. Building on prior studies, we use the log of annual wage as a dependent variable and include individual and firm characteristics such as education, experience, occupation, and industries as explanatory variables. The coefficient on Accounting Sector indicates that in comparison to other occupations, the accounting profession offers higher wages. In an untabulated result, the coefficient on External Accountant is significantly positive, indicating that even higher wages are offered to those employed in external accounting firms.[10] Since the accounting major leads to high-paying jobs, we must consider non-wage benefits to understand how individuals choose between accounting and non-accounting positions. For example, flexible working hours (and possibly remote work) could be an important factor, because employees care about non-monetary benefits (Mas and Pallais, 2017).[11] Finance & Consulting and Technology jobs also pay higher wages relative

[9] Azar et al. (2022) define the local labor market at the commuting zone level.

[10] These results align with the earlier finding of Altonji et al. (2016) that accounting graduates typically earn higher wages than the average college graduate. In fact, accounting majors are the second most highly compensated majors (Altonji et al., 2016) according to the ACS data.

[11] Poor work-life balance in public accounting is considered to be a significant factor in attracting and retaining talent to the profession (CAQ, 2023). https://www.cpajournal.com/2024/02/12/the-conflict-surrounding-work-life-balance-in-public-accounting-firms/.

to the average wage of college graduates, which suggests that industries compete for talented undergraduate students.

The coefficients of other variables in the analysis are also in line with findings from prior studies. For instance, there is a positive correlation between experience, measured as age minus years of education, and wages. Similarly, education exhibits a positive correlation with wages. This finding is consistent with the expectations of a Mincer (1958) regression model, where individuals consider the returns on education when making decisions regarding their education level. The other common determinants for wages are occupation, industry, location, and gender. The negative coefficient on Female is consistent with evidence from many industries that women on average earn lower wages. Gender differences in employment and wages in the accounting professions have received attention for many years. Table 4 indicates that gender wage differences in accounting sectors persist even in recent years (Wescott and Seiler, 1986; Hammond, 2003; Madsen, 2013). These differences are reflected in our model through wages and promotions.[12]

3 Accounting Labor Market Equilibrium Model

This section introduces a finite horizon equilibrium model to explain the interaction between individuals' dynamic decisions to pursue accounting careers and companies' evolving demand for workers. The model assumes a steady-state oligopsonistic labor market in which forward-looking workers make dynamic choices between accounting and alternative job sectors, while firms from different sectors compete for labor.

3.1 Supply of Accountants

We begin by discussing the supply of accountants. We model an individual i who chooses their job sector k among $K = 6$ mutually exclusive alternatives. These alternatives include Accounting in Big 4 (k =1), Accounting in Non-Big 4 (k =2), Internal Accountants in Other Industries (k =3), Finance & Consulting (k =4), Technology (k =5), and Non-Accounting in Other Industries or "Others" (k =6). Since we are interested in individuals' choices of job sectors, we assume that

[12] Although the accounting profession, like pharmacy, is governed by licensing regulation, promotions may be more important in accounting (Goldin and Katz, 2016).

employers within a sector are homogeneous.[13] We will therefore use the terms "jobs" and "job sectors" interchangeably hereafter.

Individuals initially differ in three dimensions. The first dimension is non-accounting education, non_acc_i, an indicator equal to one if individual i does *not* hold an accounting degree, and zero otherwise. Education reflects an individual's initial endowment of human capital and professional training related to accounting, which can impact their later career choices (Smeets et al., 2025). For instance, those without an accounting degree are more likely to face barriers to entering the external accounting profession, such as meeting CPA credit requirements (e.g., the 150-hour rule). Second, we follow Keane and Wolpin (1997) and assume that there are H types of workers with each type $h \in \{1, ..., H\}$ being endowed with a distinct set of preferences that may impact their preferences for jobs. We denote the type of individual i with h_i. Such unobserved taste heterogeneity explains why workers with the same observed characteristics often make distinct career choices. The third dimension is $master_i$, an indicator for whether an individual holds a master degree. This variable reflects an individual's ability, as those receiving a master degree typically are paid more on average.

3.1.1 Current-Period Return

The current-period return from choosing job k for individual i with a total experience t (i.e., the number of years the individual has worked since their first job, with $t = 0$ indicating no prior work experience) equals:

$$U_k(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}) = w_k(\mathbf{s}_{i,t}) + b_k(\mathbf{s}_{i,t}) + \xi_{i,j,k,t} + \theta^{-1}\epsilon_{i,k,t}. \tag{1}$$

We describe each element of the return function below.

The State Vector: The state variables are those that individuals take as given when making job choices and thus inputs to the return function (analogous to the independent variables of a regression model). These variables include (i) the individual's sector-specific work experience, $x_{i,k,t} \in \{0, ..., X\}\ \forall k$, where X is the largest possible experience; (ii) the individual's existing job, $j_{i,t} \in \{0, ..., K\}$, where $j_{i,t} = 0$ indicates that the individual does not have any prior work experience; (iii) whether the individual had experience in external accounting firms in the past, $ext\_acc_{i,t}$; (iv) whether the individual is currently a partner at a Big 4 accounting firm ($m^b_{i,t}$) or

[13] We note that our assumption of six sectors already builds in some heterogeneity within the broad accounting sector as well as within the non-accounting sector.

a partner at a Non-Big 4 accounting firm ($m^{nb}_{i,t}$); (v) the individual's total work experience t; (vi) whether an individual was not promoted to partner at a Big 4 (Non-Big 4) accounting firm in the prior year and, subsequently, faces forced turnover in the current year, denoted by f^b_{it} (f^{nb}_{it}); and (vii) job-specific shocks $\boldsymbol{\epsilon}_{i,t} \equiv (\epsilon_{i,1,t}, ..., \epsilon_{i,K,t})'$, which follow standard independent Type I extreme value distributions. The researcher does not observe (vi) and (vii). We use $\mathbf{s}_{i,t}$ to denote the vector of individual time-invariant characteristics plus the individual-level state variables:

$$\mathbf{s}_{it} \equiv \Big(non\_acc_i, h_i, female_i, master_i, x_{ikt}, j_{it}, ext\_acc_{it}, m^b_{it}, m^{nb}_{it}, f^b_{it}, f^{nb}_{it}, t\Big)'. \tag{2}$$

Wages: Individual i with a total experience t receives a wage offer $w_{i,k,t}$ when seeking a job from sector k. Section 3.2 endogenizes wages using an oligopsonistic competition model.

Non-Wage Benefits and Costs: In addition to wages, individuals also derive non-wage benefits and costs from job k, which take the form below:

$$\begin{aligned} b_k(\mathbf{s}_{i,t}) = &\sum_{l=1}^{5}\Big(\alpha_l \mathbb{1}\{k=l\}\Big) + \gamma_1 non\_acc_i \mathbb{1}\{k \leq 2\} + \sum_{h=1}^{H}\Big(\lambda_{1,h}\mathbb{1}\{h_i = h\}\mathbb{1}\{k \leq 2\}\Big) \\ &+ (\psi_1 ext\_acc_{i,t} + \psi_2 ext\_acc_{i,t} \times t)\mathbb{1}\{k \geq 3\}. \end{aligned} \tag{3}$$

First, non-wage benefits depend on time invariant sector characteristics, whose effects are captured by $\alpha_l \, \forall l$. These benefits could reflect sector-specific features that workers value such as better work-life balance (Sockin, 2022). For example, accounting jobs might carry higher non-wage benefits because of their perceived safety, which is preferred by risk averse individuals, or lower non-wage benefits due to a lack of interest in accounting work from workers. As these parameters are effectively the intercepts of a regression model, they broadly capture any time-invariant factor that influences individuals' incremental tendency to work for a particular sector, relative to working for other industries. Thus, we also refer to these parameters as "preferences."

Second, we distinguish workers' non-wage benefits and costs derived from working for external accounting sectors, relative to other sectors. This distinction is driven by our institutional setting, as external accounting jobs often require specific types of endowments (e.g., obtaining an accounting major), which are not equally distributed across the population.

Specifically, we allow non-wage benefits from external accounting jobs to depend on whether they hold accounting degrees (non_acc_i). Non-accounting majors could face frictions to enter the external accounting sector. For example, external accounting jobs often require CPA certification. While we do not directly observe CPA certification in our data, we expect a high correlation between accounting degrees and CPA qualification, as obtaining a CPA requires a minimum amount of accounting education, which can be costly to obtain for non-accounting majors. As such, the cost of non-accounting majors to enter the accounting profession might exceed that of accounting majors, implying that $\gamma_1 < 0$.

We also allow non-wage benefits from external accounting jobs to depend on individuals' unobserved tastes. Individuals with the same education might nevertheless have distinct tastes or face different frictions, resulting in different dynamic patterns of career choices. For example, some may be located in regions with limited options to obtain accounting education despite preferences for accounting jobs or live in states with more stringent CPA requirements, reducing their chance of choosing external accounting jobs. These features are captured by $\lambda_{1,h}$.

Finally, we allow individuals' past experience in external accounting firms to influence their non-wage benefits derived from working for other sectors. Individuals may value experience in the external accounting sector, as it provides them with future career benefits such as improved wages (Yang, 2024). For these individuals, they may prefer to work in the external accounting sector early in their career to accumulate human capital, implying that $\psi_1 < 0$. With sufficient human capital and the right career opportunities, they may choose other sectors later in their career. Such career switching might be reflected both in superior wages and higher amenity benefits offered by other sectors to individuals with external accounting experience. The latter effect is captured by $\psi_2 > 0$. However, it is also possible that individuals with external accounting experience receive lower amenity benefits than those without, since they lack sector-specific experience, which implies $\psi_2 < 0$. These individuals might switch from external accounting to other sectors for idiosyncratic reasons or because of forced turnover.

Structural State Dependence of Sector Choices: Individuals' non-wage benefits from choosing job k can also depend on their prior job choices in the following way:

$$\xi_{i,j,k,t} = \sum_{l=1}^{6} \left(\mathbb{1}\{k_{i,t} = j_{i,t} = l\} \times \mathbb{1}\{j_{i,t} \neq 0\} \left(\xi_0 \mathbb{1}\{x_{i,k,t} \leq 2\} + \xi_l x_{i,k,t} \right) \right). \tag{4}$$

The elements in the equation captures general continuation benefits and switching costs. Continuing the same job allows for accumulating industry-specific human capital, increasing non-wage benefits. Persistence in preferences for the prior job can also broadly capture structural state dependence in labor supply in that workers' past employment influences their current choice (Hyslop, 1999). On the other hand, switching jobs requires conducting a job search, which can be costly because of moving, the need to acquire new knowledge, and the potentially limited availability of job opportunities, which implies a longer period of costly search (Keane and Wolpin, 2001; Fox, 2010). In addition, job seekers may face geographical or family constraints preventing them from moving in general. As our switching costs may reflect these shadow costs, such as geographical constraints, their magnitudes can be significant.

These continuation benefits and switching costs may be larger for new jobs, when workers have a greater need to accumulate sector-specific human capital. We capture these effects in a reduced form using ξ_0 and expect $\xi_0 > 0$, capturing the net benefit and cost of time-series job dependence for new jobs. In addition, the continuation benefits and switching costs may also differ across sectors and over time. For example, it might be difficult for internal accounting to switch to technology given differences in the skills needed for technology jobs. Studies on labor life cycle show that individuals learn more about the matching value with their current jobs *over time* (Jovanovic, 1979). This reduction in uncertainty then incentivizes them to remain in their current job (Gorry et al., 2019). The parameters, ξ_l with $l \in \{1, ..., 6\}$, capture these effects in their reduced form with higher values indicate greater continuation benefits or switching costs.

Unobserved Idiosyncratic Tastes: Finally, individuals' job choices might also be driven by their idiosyncratic taste shocks ϵ_{ikt}. These shocks play two critical roles in the model. First, they capture *horizontal* employer differentiation. As in Lamadon et al. (2022), there are two sources of unobserved horizontal employer differentiation in our model. The first is h_i, which captures individual time-invariant heterogeneous preference for job sectors. The second source is ϵ_{ikt} with θ^{-1} capturing its importance. As θ becomes smaller, the variance of $\theta^{-1}\epsilon_{ikt}$ becomes larger. As such, horizontal differentiation becomes more important in determining the worker's preferred firm. Second, θ controls the elasticity of substitution across job sectors. This elasticity will play a critical role in determining equilibrium wages, as a greater likelihood of job switching following wage decreases limits employers' labor market power, which leads to wage increases.

3.1.2 Objective Function

Individual i with total experience t chooses from the six job sectors to maximize the sum of the expected present value of their remaining lifetime return from year t to year T with T being the horizon of the career.

Let $V_t(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t})$ be this maximum value, given the individual's state vector $(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t})'$ and the discount factor $\beta \in (0,1)$. Given a policy function $d_{kt}(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t})$, which represents an indicator for choosing job k with experience t, and collecting the policy functions corresponding to all six job choices into a vector, denoted by $\mathbf{d}_{i,t} \equiv (d_{1t}(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}), ..., d_{Kt}(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}))'$, we have

$$V_t(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}) = \max_{\mathbf{d}_{i,t},\dots,\mathbf{d}_{i,T}} \left\{ \mathbb{E}\left[\sum_{\tau=t}^{T} \beta^{\tau-t} \left(\sum_{k=1}^{K} d_{k,\tau}(\mathbf{s}_{i,\tau}, \boldsymbol{\epsilon}_{i,\tau}) U_k(\mathbf{s}_{i,\tau}, \boldsymbol{\epsilon}_{i,\tau}) \right) \right] \right\}. \tag{5}$$

Let $V_{k,t}(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t})$ be the choice-specific value function for choosing job k. For $t < T$, we can specify the choice-specific value function in the following Bellman equation:

$$\begin{aligned} &V_{k,t}(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}) \\ =&U_k(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}) + \beta \mathbb{E}\left[\max_{\mathbf{d}_{i,t+1}} \left\{ \left(\sum_{k=1}^{K} d_{kt}(\mathbf{s}_{i,t+1}, \boldsymbol{\epsilon}_{i,t+1}) V_{k,t+1}(\mathbf{s}_{i,t+1}, \boldsymbol{\epsilon}_{i,t+1}) \right) \right\} \middle| \mathbf{s}_{i,t}, k \right]. \end{aligned} \tag{6}$$

In the terminal year T, the choice-specific value function is reduced to:

$$V_{k,T}(\mathbf{s}_{i,T}, \boldsymbol{\epsilon}_{i,T}) = U_k(\mathbf{s}_{i,T}, \boldsymbol{\epsilon}_{i,T}). \tag{7}$$

3.1.3 Law of Motion

To complete the model of accounting labor supply, we need to specify the law of motion of the state vector.

The first element of the state vector is an individual's experience in job k with total experience

t, denoted as $x_{i,k,t}$. This variable increases by one year when the individual remains in the same job sector for another year. However, if they switch job sectors, where $k_{i,t} \neq j_{i,t}$ and $k_{i,t}$ represents the job choice of worker i with total experience t, we assume $x_{i,k,t+1} = 1$, and for all other jobs $k' \neq k_{i,t}$, $x_{i,k',t+1} = 0$. This assumption reflects the idea that a worker's continuous experience in their present employment sector may be more relevant to their sector choices than any previous work experience prior to their current job. Note that our model still accounts for the accumulation of general human capital that is potentially transferable across sectors, as we allow workers' productivity to depend on total experience t. The law of motion for $x_{i,k,t}$ can be summarized as follows:

$$x_{i,k,t+1} = \begin{cases} 1 + x_{i,k,t} & \text{if } k_{i,t} = j_{i,t}; \\ 0 & \text{if } k_{i,t} \neq j_{i,t}. \end{cases} \tag{8}$$

The law of motion for the second element of the state vector, namely the individual's existing job at $t+1$ or $j_{i,t+1}$, equals their job choice at t, that is, $j_{i,t+1} = k_{i,t}$. In addition, if the individual ever worked for external accounting firms in the past, $ext\_acc_{i,t} = 1$, and zero, otherwise.

The law of motion for whether the individual is a partner at a Big 4 accounting firm, denoted as m^b_{it}, depends on $\mathbf{s}_{it}$ and the characteristics of individual i. Specifically, an individual can become a partner in the following year with probability $\Phi_i(\mathbf{s}_{it})$ only if they have greater than or equal to nine years of total experience.[14] Otherwise, they are not eligible to become a Big 4 partner. We non-parametrically estimate these probabilities from the data.

$$m^b_{i,t+1} = \begin{cases} \Phi^b_i(\mathbf{s}_{it}) & \text{if } t \geq 9; \\ 0 & \text{if } t < 9. \end{cases} \tag{9}$$

Similarly, the law of motion for $m^{nb}_{i,t}$ also depends on $\mathbf{s}_{it}$ and the characteristics of individual i:

$$m^{nb}_{i,t+1} = \begin{cases} \Phi^{nb}_i(\mathbf{s}_{it}) & \text{if } t \geq 9; \\ 0 & \text{if } t < 9. \end{cases} \tag{10}$$

Individuals may face forced turnover if they were not promoted to partner in the previous

[14] We choose nine years based on the data analyses in the online appendix.

year. We use the indicators f_{it}^{b} and f_{it}^{nb} to represent instances of forced turnover, which occur with probabilities ζ_b and ζ_{nb}, respectively. Specifically, individuals who were not promoted to Big 4 (Non-Big 4) partners in the prior year have to move to one of the five remaining sectors (e.g., Internal Accounting) with probability ζ^b (ζ^{nb}). They have the option of remaining with the Big 4 (Non-Big 4) with probability $1 - \zeta^b$ (1-ζ^{nb}). Since we focus on job sector choices, our model and estimation only capture the likelihood of being forced to transition to *other job sectors*, for example, leaving Big 4 accounting firms to join Non-Big 4 firms.

Finally, the choice-specific random shocks, $\boldsymbol{\epsilon}_{i,k,t}$, are cross-sectionally and intertemporally independent and are independent across alternatives. This assumption is conventional in dynamic discrete choice models and is essential for the viability of estimating our model, which accommodates both structural state dependence and dynamics.[15]

3.2 Demand for Accountants

There are $M_{i,k,t}$ number of identical firms in sector $k \in \{1, ..., K\}$, competing for workers with characteristics $\tilde{\mathbf{s}}_{it}$. We use $\tilde{\mathbf{s}}_{it}$ to denote worker observable characteristics, excluding forced turnover (f^b and f^{nb}) and worker types (h). Firm l in sector k maximizes the profits by offering a wage $w_{i,t,l}$ to individuals with characteristics $\tilde{\mathbf{s}}_{it}$, taking into account (i) potential job seekers' supply of labor (i.e., how their labor supply varies with wages), and (ii) wage offers by firms within the same sector and those from the other sectors competing for the same labor pool ($w_{i,-l,t}$).

$$max_{w_{i,l,t}\forall i,t} \int \left\{ \underbrace{\nu_k\Big(\iota_k(w_{i,l,t};\tilde{\mathbf{s}}_{it}, w^*_{i,-l,t})\Big)}_{\text{Revenue}} - \underbrace{w_{i,l,t} * \iota_k\left(w_{i,l,t};\tilde{\mathbf{s}}_{it}, w^*_{i,-l,t}\right)}_{\text{Cost}} \right\} d\Gamma(\tilde{\mathbf{s}}_{it}), \qquad (11)$$

where $\iota_k(w_{i,l,t};\tilde{\mathbf{s}}_{it}, w^*_{i,-l,t})$ is the number of workers with characteristics $\tilde{\mathbf{s}}_{it}$ choosing to work for firm l, given the equilibrium wages offered by competing firms ($w^*_{i,-l,t}$); $\nu_k(\iota_k)$ is the revenue generated from hiring these workers; and $\Gamma(\tilde{\mathbf{s}}_{it})$ represents the distribution of workers with characteristics

[15] Bernhardt et al. (2016) discuss on page 999 why a model with serial correlation in error terms cannot be estimated using traditional approaches even in a simple regression framework without explicitly computing expected future utility. Roughly, when error terms are serially correlated, the current-period error term and prior job choices are not independent conditional on other observed determinants of current-period job choices. Hence, the likelihood function needs to integrate over the entire history of error terms for all observations in the data. Maximum likelihood estimation is not feasible.

$\tilde{\mathbf{s}}_{it}$. As wage offers of one firm take as given those of competing firms, we effectively model an oligopsonistic labor market.[16]

The number of workers with characteristics $\tilde{\mathbf{s}}_{it}$ choosing to work for firm l is specified as follows:

$$\iota_k(w_{i,l,t}; \tilde{\mathbf{s}}_{it}, w^*_{i,-l,t}) \equiv N(\tilde{\mathbf{s}}_{it}) \underbrace{\hat{\eta}_k(w_{i,l,t}; \tilde{\mathbf{s}}_{it}, w^*_{i,-l,t})}_{\text{Prob of choosing sector } k} \underbrace{\rho_k(w_{i,l,t}; \tilde{\mathbf{s}}_{it}, w^*_{i,-l,t})}_{\substack{\text{Prob of choosing firm } l \\ \text{conditional on choosing sector } k}}, \tag{12}$$

where $N(\tilde{\mathbf{s}}_{it})$ is the total number of workers in the labor market with characteristic $\tilde{\mathbf{s}}_{it}$, $\hat{\eta}_k(.)$ represents the share of workers with characteristics $\tilde{\mathbf{s}}_{it}$ choosing to work in firm l's sector, and $\rho_k(.)$ captures the probability that workers end up being matched to firm l *conditional on* choosing to work in firm l's sector.

Firms in our model engage in labor market competition, taking as given their labor supply curve and competing wage offers. The specification of the labor supply in equation (12) implies two effects associated with a marginal wage increase by firm l. First, it increases the likelihood of workers choosing sector k by $\frac{\partial \hat{\eta}_k}{\partial w_{i,l,t}}$ with the following specification,

$$\frac{\partial \hat{\eta}_k(w_{i,l,t}; \tilde{\mathbf{s}}_{it}; w^*_{i,-l,t})}{\partial w_{i,l,t}} \approx \frac{\partial \hat{\eta}_k(w^*_{i,k,t}; \tilde{\mathbf{s}}_{it})}{\partial w^*_{i,k,t}} \Delta^b_{i,k,t}. \tag{13}$$

The derivative $\frac{\partial \hat{\eta}_k(w^*_{i,k,t}; \tilde{\mathbf{s}}_{it})}{\partial w^*_{i,k,t}}$ captures the effect of wage increases by *all* firms in the sector on workers' sector choice. In reality, it is possible that a marginal wage increase by one of the firms in the sector, which is what determines the equilibrium wage, generates a smaller effect. For instance, suppose one of the Non-Big 4 accounting firms increases its wage offer. The likelihood that this increase will attract workers into the Non-Big 4 sector might be smaller than the case in which there is only one large non-Big 4 accounting firm and this employer increases wages. We assume that this moderating effect varies with the number of firms, that is,

$$\Delta^b_{i,k,t} = e^{-\chi_1(M_{i,k,t}-1)}, \tag{14}$$

[16] Although our labor demand is static, we would get the same solution if employers of each sector maximized the sum of discounted future profits taking as given a steady state distribution of employee characteristics. Such a steady state distribution can arise if we combine our model of labor supply with exogenous entries and exits of workers of each type. We assume the existence of this distribution and abstract away from explicitly modeling these forces, as they further complicate the estimation. We also abstract away from interactions among workers for the same employer, such as complementarities in their productivity.

where $M_{i,k,t}$ is the number of firms in sector k faced by individuals with characteristic $\tilde{\mathbf{s}}_{it}$.

Second, a marginal wage increase by firm l increases the likelihood that employees are matched to firm l given that they have chosen sector k. We assume that this marginal impact equals

$$\frac{\partial \rho_k(w_{i,l,t}; \tilde{\mathbf{s}}_{it}, w^*_{i,-l,t})}{\partial w_{i,l,t}} \approx \Delta^w_{i,k,t} \equiv \frac{1}{M_{i,k,t}} \frac{M_{i,k,t}-1}{M_{i,k,t}} * \chi_2, \tag{15}$$

where $\chi_2 > 0$. Under the assumption that the matching technology between employers and workers follows a simple logit specification, the impact of a marginal wage increase by one employer who competes with $M_{i,k,t} - 1$ other identical employers would equal $\frac{1}{M_{i,k,t}} \frac{M_{i,k,t}-1}{M_{i,k,t}}$. We use parameter χ_2 to capture possible deviations from this benchmark. For example, it is possible that not all employers are hiring in a year, or that some employers face less matching friction than others (e.g., they are more visible to workers than others).

Given the specification of labor demand above, workers in our model face a non-competitive labor market (Berger et al., 2022; Lamadon et al., 2022; Yeh et al., 2022). On the one hand, employers have market power because individuals have heterogeneous tastes in occupational choices. This heterogeneity implies an upward sloping labor supply curve that employers internalize when offering wages, which leads to wage markdowns. For example, knowing that certain individuals prefer to work in accounting jobs and are willing to accept a lower wage, employers will reduce the wage offer to maximize profits. On the other hand, employers compete for the same labor pool with other employers in the same sector as well as with employers in other sectors, in the spirit of Berger et al. (2022). Such competition generally increases wages because it gives workers the option to switch to other jobs.

Firm l faces standard trade-offs that characterize non-competitive labor markets. A higher wage offer attracts new workers to the firm, increasing its revenue, $\nu'_k(\iota_{i,k,t}) > 0$, but it is costly because all workers with the same characteristics receive higher wages, driving up labor costs. For tractability, we assume that $\nu_k(\iota_{i,k,t})$ can be approximated by a linear function:

$$\nu_k\Big(\iota_k(w_{i,k,t}; \tilde{\mathbf{s}}_{it}, w_{i,-k,t})\Big) = \nu_0 + \nu_k(\tilde{\mathbf{s}}_{it}) N(\tilde{\mathbf{s}}_{it}) \hat{\eta}_k(w_{i,k,t}; \tilde{\mathbf{s}}_{it}, w_{i,-k,t}) \rho_k(w_{i,k,t}; \tilde{\mathbf{s}}_{it}, w_{i,-k,t}). \tag{16}$$

We further assume that the marginal revenue product of labor in sector k, denoted as $\nu_{i,k,t}$, varies with an individual's total experience and a subset of their characteristics ($\tilde{\mathbf{s}}_{it}$). Specifically, workers with more experience are expected to be more productive than younger, less experienced workers. We also attempt to capture observed heterogeneity in labor productivity due to individual characteristics, including whether they hold a master degree or an accounting degree. To capture the possible selection effect of individuals who choose external accounting jobs, we allow the productivity of these individuals to differ.

Additionally, we assume that both firms and employees observe the current $\nu_{i,k,t}$ and form rational expectations about future $\nu_{i,k,t}$ before making their decisions. As we rely on estimated wage for estimation and these wages, by construction, only depend on observed characteristics, we assume that employers do not offer different wages depending on whether workers experience forced turnovers or whether they are of a certain type. We also do not model partner wages, as there are few of them and they are technically the employer.

The first order condition of firm l gives rise to the labor demand curve:

$$\begin{aligned} &\frac{(\nu_{i,k,t} - w_{i,k,t})\theta\Delta^b_{i,k,t}\left(\sum_{h=1}^{H}\pi_h\hat{\eta}^{(h)}_{i,k,t}(1-\hat{\eta}^{(h)}_{i,k,t})\right) - \hat{\eta}_{i,k,t}}{M_{i,k,t}} \\ &+ (v_{i,k,t} - w_{i,k,t})\hat{\eta}_{i,k,t}\Delta^w_{i,k,t} = 0 \\ \Longrightarrow & w_{i,k,t} = \nu_{i,k,t} - \underbrace{\frac{1}{\frac{\sum_{h=1}^{H}\pi_h\hat{\eta}^{(h)}_{i,k,t}(1-\hat{\eta}^{(h)}_{i,k,t})}{\hat{\eta}_{i,k,t}}\theta e^{-\chi_1(M_{i,k,t}-1)} + \frac{M_{i,k,t}-1}{M_{i,k,t}} * \chi_2}}_{\equiv \mu_{i,k,t}}, \end{aligned} \tag{17}$$

where θ captures the importance of idiosyncratic taste shocks; $\hat{\eta}^{(h)}_{i,k,t}$ represents the labor market share of individuals with type h and observed characteristics $s_{i,k,t}$. The derivation utilizes the fact that, due to the Type I extreme value model, the derivative of labor supply at the sector level with respect to wage equals $\theta\hat{\eta}_{i,k,t}(\mathbf{s}_{i,t})(1-\hat{\eta}_{i,k,t}(\mathbf{s}_{i,t}))$.[17]

Equation (17) shows that labor demand is driven by three factors. First, a greater marginal revenue product of labor increases labor demand, pushing up wages (holding labor supply constant). In a competitive labor market, wages equal the marginal product of labor, which we will use as a benchmark to evaluate employers' market power.

[17] The derivation also utilizes the fact that conditional on the state vector $\mathbf{s}_{i,t}$ and the individual's job choice k, the expected future return for the individual conditional on choosing k is independent of $w_{i,k,t}$. Thus, the derivative of $\hat{\eta}_{i,k,t}(\mathbf{s}_{i,t})$ with respect to $w_{i,k,t}$ only needs to account for $U_{i,k,t}$ in Equation 18.

Second, employees may be paid less than their marginal revenue product of labor. The degree of this markdown, or the employer's monopsony power, increases with the market share of the sector and with the importance of workers' idiosyncratic taste shocks (i.e., θ^{-1}). Intuitively, holding everything else equal, a greater market share of a sector implies higher costs of switching from that sector to others, giving employers greater bargaining power over wages. Holding constant employees' willingness to supply labor, as workers have more diverse preferences for different employers, they are more likely to switch to other sectors when being offered a lower wage, reducing the ability of their employers to offer lower wages.

Finally, employers' oligopsony power is shaped by both within-sector and across-sector competition. While research has studied within-sector competition (e.g., within Big 4 audit firms), across-sector competition has not been considered. Specifically, the presence of more employers in a sector increases competition among each other for labor, reducing the equilibrium wage markdown. The intensity of this effect is captured by $\frac{M_{i,k,t}-1}{M_{i,k,t}} * \chi_2$. However, the presence of more employers in a sector also implies that each employer is less likely to internalize the impact of its own wage decreases on the sector-level employment, which increases wage markdowns. The intensity of this effect is captured by $e^{-\chi_1(M_{i,k,t}-1)}$.

3.3 Equilibrium and Discussion

We focus on a symmetric steady state rational expectations equilibrium of the labor market. In this equilibrium, all companies look for workers simultaneously. Given the wage offers by the employers, all individuals make their labor market decisions at the same time. We define the labor market equilibrium as follows:

Definition 1. Steady State Rational Expectations Equilibrium

The labor market equilibrium satisfies five conditions:

(i) *Dynamic labor supply*:

Employees with characteristics $\mathbf{s}_{it}$ choose which sector to work in to maximize (5), given their state vector $(\mathbf{s}'_{it}, \boldsymbol{\epsilon}'_{it})'$, the discount factor $\beta \in (0, 1)$, and the wage offers from employers of different sectors $\mathbf{w}_{it}$. The resulting labor market supply share of sector k, integrated over the choice-specific shocks $\boldsymbol{\epsilon}_{it}$, is denoted by $\eta^*_k(\mathbf{s}_{it}, \mathbf{w}_{it})$.

(ii) *Labor market demand*:

Firm l in sector k maximizes its profit in (11) by choosing a wage offer for employees with characteristics $\tilde{\mathbf{s}}_{it}$, taking as given the labor supply curve implied by (i), that is, $\eta_k^*(\mathbf{s}_{it}, \mathbf{w}_{it})$, and the equilibrium wage offers from competing employers within and across sectors.

(iii) *Market clearing*:

The wage offers of employers to workers with characteristics $\tilde{\mathbf{s}}_{it}$, $\mathbf{w}_{it}$ induce the labor supply of that sector $\eta_k^*(\mathbf{s}_{it}, \mathbf{w}_{it})$, as defined in (i). The total employment across sectors equals the total number of workers in the economy.

(iv) *Symmetric equilibrium*:

Employers in the same sector offer the same wage to workers with characteristics $\tilde{\mathbf{s}}_{it}$.

(v) *Rational expectation for the steady state*:

All employees monitor the prevailing labor market conditions for all $\mathbf{s}_{it}$'s and form rational expectations about $\mathbf{s}_{it}$, the laws of motion.

In equilibrium, five conditions must hold. First, employees optimally choose job sectors given wage offers from employers. Second, the wage offers by a sector must be consistent with those offered by other sectors. A necessary condition is therefore that the equilibrium wage offers satisfy the labor demand function in equation (17). As there are six sectors, we have six equations corresponding to the wage offers for each of the six sectors. These six equations characterize the oligopsonistic competition for labor. Third, labor supply and demand must equal each other. In addition, the wage offers chosen by firms in each sector must induce the same labor supply that is used as the input to determining the wage offers of that sector. Fourth, we focus on symmetric equilibrium within firms in a sector, as these firms are assumed to be ex-ante identical and to behave in the same way. Finally, all employees observe the current labor market conditions for all $\mathbf{s}_{it}$'s and form rational expectations about their future evolution. In sum, the equilibrium of the model is characterized by 12 functional equations: (i) the market clearing condition for wage offers equating labor supply and demand for each of the six sectors and (ii) the first order conditions for wage offers in each of the six sectors.

Our equilibrium allows for oligopsonistic labor markets in which employers make non-zero profits. A snapshot of this market equilibrium is illustrated in Figure 3. The figure showcases a monopsony equilibrium (W_M, L_M) in the labor market. With monopsony, a firm has the power to set wages in the labor market and adjust wages in order to affect equilibrium labor inputs. The marginal factor cost of acquiring one more unit of labor is higher than the wage at which the unit is acquired because the firm needs to pay higher wages for all employees given an upward sloping labor supply curve. A monopsony firm hires the amount of a labor input such that the marginal revenue product is equal to the marginal factor cost of labor, internalizing an upward sloping labor supply curve. The corresponding higher marginal cost associated with a unit increase of labor implies that firms that maximize their profits set wages below the competitive wage level. Compared to competitive markets, monopsony markets end up with lower wages, i.e., $W_M < W_C$, and less labor hiring, i.e., $L_M < L_C$, and the latter can lead to market perceptions of "a supply shortage." The wage markdown $\mu_{i,k,t} = \nu_{k,t} - W_M$ measures firms' labor market power in sector k.

4 Identification and Estimation

4.1 Identification

Heckman (1979) and Heckman and Singer (1984) first described the general approach for including multinomial types in longitudinal models. Keane and Wolpin (1997) initially applied the estimation approach to discrete choice dynamic programming (DCDP) models with fixed types. Because the model has a finite horizon, it is possible to identify some of the model parameters using the last time period. Wages are estimated from Current Population Survey to supplement the resume data. As such, our wage estimates depend on only observed employee characteristics. We assume that individuals choose sectors before the wage shocks are realized (or that our estimated wage is an offered wage). As a result of this timing assumption, there is no issue with selection in estimating the wage equation.

As shown in Section 3.1.2, in the last period, the decision problem is reduced to a static discrete choice model. Horowitz (1981) discusses how to identify such models. The observed choices allow us to deduce relative but not absolute utilities. Therefore, identification requires normalizing one of the return values. Given our objective of comparing accounting jobs with non-accounting ones, we normalize the non-monetary reward of other industries to be zero.

The nonpecuniary benefits from occupational choices are identified from differences in the choice probabilities conditional on the same wage. When two jobs offer identical wages but Job A is deemed preferable to Job B, the estimated non-wage benefits for Job A surpass those for Job B. Specifically, individuals' job-switching patterns along their career paths identify the parameters characterizing job-switching utilities, while the parameters for sector-specific preferences are identified from initial job choices, which don't incur job-switching costs. Differences in conditional choice probabilities by type (e.g., non_acc_i) reveal the type-specific components of the current-period return.

Unobserved time invariant taste differences (i.e., individual types) are identified from the differences in labor market choices across individuals with the same characteristics. In addition, one of the type-specific intercepts $\lambda_{1,h}$ needs to be normalized, as they are collinear with the sector-specific preferences α_k. We normalize $\lambda_{1,1} = 0$. As such, the preference of type 1 individuals for external accounting jobs is captured by the intercept, α_1 and α_2.

The parameter capturing the importance of idiosyncratic shocks (i.e., θ^{-1}) is identified from the sensitivity of job choices to wages in labor supply in (1) as well as the sensitivity of wages to labor demand in (17). The presence of labor demand is important for identification. Observed differences in wages across jobs might be small due to competition across sectors. Thus, employment decisions may appear to be insensitive to wages, creating a downward bias in θ. The labor demand model corrects for the bias because a low wage sensitivity implies lower wage levels, as shown in (17). The estimated θ balances its impact on wage levels with the sensitivity of labor supply to wages.

Finally, marginal product of labor is identified from sector-experience variation in wages. The parameters that affect the degree of oligopsony, χ_1 and χ_2, are identified from the sensitivity of wages to the number of employers of each sector. Forced turnover rates are identified from switching patterns when employee tenure at the external accounting firms exceeds nine years, the year in which partner promotion becomes possible given our model assumption.

4.2 Estimation

Our model parameters are estimated by maximizing the likelihood of observed career choices:

$$\max_{\Theta}\left\{\left(\prod_i\left[\sum_{h=1}^{H}\pi_{ih}\prod_{t=0}^{T}\left(\prod_l \Pr\{d_{i,l,t}(\Theta;\tilde{\mathbf{s}}_{i,t},w_{i,l,t}\forall l,h_i)=1\}^{\mathbb{1}\{l=k_{i,t}\}}\right)\right]\right)\left(\prod_{i,k,t}f(w_{i,k,t}(\Theta))|\tilde{\mathbf{s}}_{i,t}\}\right)\right\}. \tag{18}$$

We use Θ to denote the vector of parameters to estimate, which is chosen to maximize (18). The likelihood function consists of two parts. The first is the likelihood function of individuals' job choices with k_{it} being the *actual* choice made by individual i with total experience t. This likelihood is conditional on the characteristics of individual i with total experience t observed by the econometrician, denoted by $\tilde{\mathbf{s}}_{i,t}$. As such, the choice probabilities in the first term of the expression are after integrating the forced turnover outcomes, conditional on the individual's type (h_i). As individuals' types are not observed by the econometrician, we also need to integrate them out of the likelihood function. We use π_{ih} to denote the probability that individual i is of type h, which assumes to vary with whether i obtains an accounting degree.

The second part of the likelihood function of wages is $f(w_{i,k,t}(\Theta))$. We exclude wages offered by other industries from the likelihood function. As we do not model the detailed industrial structure of that sector, that is, Sector Six might include many sub-industries that compete for labor, the wage model is likely misspecified for that sector. A consequence of this choice is that we cannot recover the marginal product of labor for that sector.

Evaluating the likelihood function requires computing the likelihood of job choices conditional on individual characteristics (including those not observed by the econometrician), $\Pr\{d_{kt}(\Theta;\mathbf{s}_{i,t},w_{i,k,t}\forall k)=1\}$, which takes two steps. The first step is to derive the current-period return and value functions before the individual observes the job-specific shocks, $\boldsymbol{\epsilon}_{i,t}$. As standard Type I extreme value distributions have simpler expressions, we multiply the labor return functions by θ and denote the resulting object as the lower case, that is, $u_k(_{it})\equiv\theta U_k(_{it})$ and $v_{kt}(_{it})\equiv\theta V_{kt}(_{it})$. We add upper bars to differentiate these functions from the functions after the individual observes the job-specific shocks as defined above. Specifically, for $t < T$, we have

$$
\begin{aligned}
v_{kt}(\mathbf{s}_{i,t}, \boldsymbol{\epsilon}_{i,t}) &= \bar{v}_{kt}(\mathbf{s}_{i,t}) + \epsilon_{i,k,t} \\
=&\bar{u}_k(\mathbf{s}_{i,t}) + \epsilon_{i,k,t} + \beta \mathbb{E}\left[\max_{\mathbf{d}_{i,t+1}} \left\{ \left(\sum_{k'=1}^{K} d_{k',t+1}(\mathbf{s}_{i,t+1}, \boldsymbol{\epsilon}_{i,t+1}) \Big(\bar{v}_{k',t+1}(\mathbf{s}_{i,t+1}) + \epsilon_{i,k',t+1} \Big) \right) \right\} \Bigg| \mathbf{s}_{i,t}, k \right].
\end{aligned}
\tag{19}
$$

Assuming that $\epsilon_{i,k,t}$ follows a standard Type I extreme value distribution, the choice-specific value function for $t < T$ can be re-expressed using

$$
\bar{v}_{kt}(\mathbf{s}_{i,t}) = \bar{u}_k(\mathbf{s}_{i,t}) + \beta \mathbb{E}\left[log \left(\sum_{l=1}^{K} e^{\bar{v}_{l,t+1}(\mathbf{s}_{i,t+1})} \right) + \gamma \Bigg| \mathbf{s}_{i,t}, k \right], \tag{20}
$$

where γ represents the Euler's constant.

For a given set of model parameters, Θ, all choice-specific value functions can then be derived using backward induction. Equation (7) directly produces the choice-specific value functions for $t = T$. Moving back one year to year $T - 1$, we have

$$
\bar{v}_{kt}(\mathbf{s}_{i,T-1}) = \bar{u}_k(\mathbf{s}_{i,T-1}) + \beta \mathbb{E}\left[log \left(\sum_{l=1}^{K} e^{\bar{u}_l(\mathbf{s}_{i,T})} \right) + \gamma \Bigg| \mathbf{s}_{i,T-1}, k \right]. \tag{21}
$$

With $\bar{V}_k(\mathbf{s}_{i,T-1})$, we can derive $\bar{V}_k(\mathbf{s}_{i,T-2})$ and so on through further backward inductions.

In the second step, we can derive the probability of choosing job k in year t using the choice-specific value functions:

$$
\eta_k(\mathbf{s}_{it}) \equiv \Pr\{d_k(\mathbf{s}_{i,t}) = 1\} = \frac{e^{\bar{v}_{kt}(\mathbf{s}_{i,t})}}{\sum_{l=1}^{K} e^{\bar{v}_{lt}(\mathbf{s}_{i,t})}}. \tag{22}
$$

4.2.1 The Curse of Dimensionality

Given the dynamic nature of job choices, estimating the model is computationally demanding because of the need to compute all possible future career paths in a finite horizon model. This problem is known as the curse of dimensionality. To illustrate, consider an individual who is expected to work for 30 years. Ex ante, there are $6^{30} \approx 2.2 \times 10^{11}$ *trillion* possible future paths to consider and evaluate. Solving a dynamic model of such a scale is not only computationally infeasible but also unlikely to approximate actual human behavior well. Adding more determinants will exponentially increase the computation burden. For example, accounting for differences in individual types (e.g., whether they obtain their accounting degree) requires separate evaluations of future career paths for each type, which will increase the computational burden from 6^{30} to $2 * 6^{30}$, or 4.4×10^{11} *trillion*.

Addressing the curse of dimensionality necessitates a simple model. In our setting, individuals choose their current job sector anticipating its effects on their accumulation of sector-specific experiences. Thus, sector-specific experiences are the minimal element needed to answer our research question. We further simplify the model by differentiating individuals only by gender and whether they have an accounting degree and limiting their horizon to 20 years after the start of their career (i.e., 21 years in total). Switching job sectors happens relatively infrequently after 20 years, and many of the partner promotions have already happened by this point (e.g., it takes an average of 12 years to be promoted to partner in an external accounting firm (Hairston et al., 2019)). Thus, the 20-year limit allows us to capture meaningful variation in sector switching and partner promotion.

However, even with the restriction on time horizon, individuals have about $6^{21} \approx 2.2 \times 10^4$ *trillion* possible career choices over a 21-year horizon. Therefore, it would not be feasible to keep track of sector-specific experiences for all six sectors. Doing so which would require a $6^{21} \times 6$ dimensional matrix even before accounting for heterogeneity across individuals. We deal with this problem by resetting individuals' job-specific experience to zero once they switch to a different *sector*. By doing so, we only need to keep track of experience in the current sector, which takes a maximum of 21 levels. While somewhat restrictive, the specification captures the first order determinant of job sector choices and makes it feasible to estimate the model and include heterogeneity in individual characteristics, which are important factors for individuals' labor supply decisions.

To further alleviate the the curse of dimensionality problem, we eliminate states that never appear in the data. For example, the prior job of a Big 4 partner with a 20-year total experience is never from Non-Accounting Other Industry ($k = 6$). We thus eliminate this state from the computation, implicitly assuming that the sector was not an option for that individual. This restriction is in a similar spirit to the zero offer probability restriction imposed by Sauer (1998), who studies the market for lawyers. We also only accommodate two unobserved types for individuals, that is, $H = 2$. As such, we estimate the following non-wage benefits and costs:

$$b_k(\mathbf{s}_{i,t}) = \sum_{l=1}^{5} \left(\alpha_l \mathbb{1}\{k = l\} \right) + \gamma_1 non\_acc_i \mathbb{1}\{k \leq 2\} \\ + (\psi_1 ext\_acc_{i,t} + \psi_2 ext\_acc_{i,t} \times t)\mathbb{1}\{k \geq 3\} + \lambda_1 \mathbb{1}\{h_i = 2\}\mathbb{1}\{k \leq 2\}. \tag{23}$$

5 The Labor Market for Accountants

5.1 Data

We use the Revelio data as the primary dataset for estimating our dynamic career choice model of business graduates including accounting graduates. The labor market data utilize tens of millions of LinkedIn profiles to construct four main components: job profiles, education, individual characteristics, and employer profiles. The data vendor uses machine learning to classify job titles and industries into the Standard Occupation Classification (SOC) and North American Industry Classification System (NAICS), which is a part of the employer profile. When the data vendor infers occupation, it uses individual-level information such as the description of the job. We identify partners at accounting firms based on their job titles. The education variables include school, major, and starting and ending years. The individual characteristics include inferred gender, race, and ethnicity. The inference is based on the name and location using a method that has been validated in prior studies (Choi et al., 2023; Sutherland et al., 2024; Baker et al., 2024).

Our sample selection criteria are as follows. We focus on college students majoring in business, including accounting as a subfield, at the bachelor's or master's level, as our analysis in Section 2.2 indicates that accounting firms often hire non-accounting majors. Our data include individuals who began their careers in or after 1994. As we track everyone over a 21-year period, workers appearing earlier in the sample period are generally younger. For instance, individuals in 1995 would have at most one year of experience. To mitigate this bias in our sample composition, we limit our sample to career choices made between calendar years 2014 and 2022 (the last year for which we have complete data), ensuring that individuals with up to 20 years of total experience at the start of each year are represented throughout our sample period. This allows us to empirically study the steady state distribution of accounting labor supply.

Then, for each year following the start of an individual's career, we classify their prior job sector and current job sector using the resume data. We define sectors based on the combination of occupation and industry information. As external accounting firms often have both accounting and consulting/advisory arms, we classify only individuals who perform auditing or assurance work for external accounting firms into the external accounting sectors. Based on their sector choices, we compute their sector-specific work experience ($x_{i,k,t}$), their overall work experience (t), and the job sector of the position held in the previous year ($j_{i,t}$). We also collect data on whether individuals are partners of Big 4 accounting firms ($m^{b}_{i,t}$) or Non-Big 4 accounting firms ($m^{nb}_{i,t}$). We obtain wage data from the Current Population Survey (CPS) and merge the data with Revelio to obtain average individual characteristics missing from CPS. To reduce noise in the wage data and be consistent with our model, our empirical analysis uses the average wage for a given combination of sector and individual characteristics. We infer these average wages using Random Forest, a machine learning model that allows for interactions and non-linear relations.

5.2 Summary Statistics

Table 5 displays summary statistics for the variables used in our empirical analyses. Regarding job sector choices, approximately 2% choose to work for public accounting firms, 6% pursue Internal Accounting jobs, 19% go into Finance & Consulting, and 10% opt for Technology. The remaining 63% work in other industries.[18]

Regarding worker characteristics, Revelio identifies approximately 44% of workers (i.e., business graduates) as female. About 92% of workers do not hold an accounting degree. The average worker earns approximately $90k per year with about 8.2 years of total work experience and 6.8 years of sector-specific work experience. These data suggest that sector switching is uncommon.

Next, we investigate workers' wage profiles across sectors in Figure 4, documenting significant wage heterogeneity across sectors. The Finance & Consulting sector typically offers the highest wages, followed by those offered by the Big 4 and Technology sectors. Internal Accounting and Non-Big 4 positions have lower wages than these three sectors, but they still offer higher wages

[18]The labor market share statistics are similar when we use data from the American Community Survey. Restricting the sample period to 2014 to 2022, we find that 3.4% of workers with business degrees choose to work for public accounting firms, 8.3% pursue Internal Accounting jobs, 16% go into Finance & Consulting, and 8% opt for Technology. The remaining 65% work in other industries.

than non-accounting jobs in other industries. This wage disparity persists throughout workers' careers, with two key exceptions: wages in Big 4 firms surpass those in Technology after 10 years of experience, and wages in Non-Big 4 positions exceed those in Internal Accounting after six years of experience. These results highlight the potential for forward-looking career decisions based on future wage dynamics.

5.3 The Importance of Dynamic Incentives and Model Fit

Table 6 Panel A decomposes the variance of choice-specific value functions into current-period return to labor and expected future return. We find that current-period return accounts for 2% of the variation in the choice-specific value function and that expected future return is responsible for the remaining 98%. The results suggest that it is important to consider forward-looking incentives when modeling workers' sector choices. Further analysis (untabulated) shows that within the current-period return function, idiosyncratic taste shocks $\epsilon_{i,k,t}$ account for 48% of the variance, suggesting the importance of accounting for these shocks. Table 6 Panel B examines the model fit. Overall, the model preserves the ordering of individuals' choices of the six job sectors.

5.4 Labor Supply

5.4.1 Parameter Estimates

Table 7 presents the parameter estimates of our dynamic career choice model described in Section 3. Panel A reports those related to non-wage benefits. Two results are worth noting.

First, individuals without prior work experience perceive accounting jobs—especially in external accounting—as offering lower non-wage benefits compared to other sectors. Specifically, accounting majors with no work history (i.e., $e = 0$ and $j_{it} = 0$) believe that Finance/Consulting jobs provide the highest non-wage benefits, exceeding those in Technology and Internal Accounting by \$10k and \$12k, respectively ($\alpha_3 - \alpha_4$ and $\alpha_5 - \alpha_4$). Among individuals of the first unobserved type ($h_i = 1$), Finance/Consulting roles are perceived to offer non-wage benefits that are \$52k and \$24k higher ($\alpha_1 - \alpha_4$ and $\alpha_2 - \alpha_4$) than those in Big 4 and non-Big 4 accounting firms, respectively. This perception is even more negative among individuals of the second unobserved type ($h_i = 2$), who view external accounting jobs as offering \$71k less (λ_1) in non-wage benefits than the baseline group of the first unobserved type ($h_i = 1$).Similarly, individuals without an accounting degree perceive external accounting roles to offer \$18k less (γ_1) in non-wage benefits than those with an accounting degree.[19]

These results suggest entry frictions to the accounting profession, particularly external accounting jobs. Such frictions may reflect workers' distaste for accounting jobs due to the restrictive nature of accounting tasks (Le, 2025), consistent with their endogenous choice of a non-accounting degree. They might also capture institutional entry barriers to accounting jobs for those without an accounting degree. For instance, the 150-hour rule could deter some individuals from pursuing employment at external accounting firms that require the CPA qualification.

Second, individuals with prior external accounting experience perceive that this experience leads to non-wage benefits that are *lower* by \$45k ($\psi_1 < 0$) when they choose *non-external accounting* jobs than when they choose *external accounting* jobs. This negative perception increases over their work experience, although the degree of increase is small, roughly about \$181 per year. This result is in contrast with untabulated evidence that individuals with external accounting experience earn higher wages conditional on their work experience and jobs. Thus, while external accounting experience helps increase workers' productivity, increasing their wages, it is not perceived by workers to offer greater non-wage benefits when they transition to other sectors, perhaps related to the nature of jobs they perform even after transitioning.

Panel B reports parameter estimates regarding structural state dependence. In general, individuals perceive benefits of staying in their jobs in general ($\xi_1, ..., \xi_6 > 0$) and particularly at the beginning ($\xi_0 > 0$). The results are consistent with life-cycle models in which workers learn about their matching value with their jobs, and the decrease in uncertainty increases the value of staying in the same job (Gorry et al., 2019). In addition, structural state dependence might capture geographic or family frictions preventing workers from moving in general, which we do not model explicitly. As such, these benefits may also capture shadow costs of switching jobs, not necessarily benefits of staying. In terms of the economic magnitude, each incremental year of work experience is associated with \$11k to \$24k non-wage benefit.

[19] Glassdoor offers a number of rating categories that shed light on employees' assessments of their work experience: Culture & Value, Diversity & Inclusion, Work-Life Balance, Senior Management, Compensation and Benefits, and Career Opportunities. The data for Deloitte as of January 10, 2024 show that Work-Life Balance is the lowest (3.2) and Career Opportunities is highest (4.2).

5.4.2 The Career Value of Accounting Education and Experience

Our model allows us to estimate workers' life-time career value at any point in time (up to a 20 years after graduation). Mathematically, the value equals

$$\log\left(\sum_{k=1}^{6} e^{V_{i,k,t}} + \theta^{-1}\gamma\right), \tag{24}$$

where $V_{i,k,t}$ is the choice-specific value function for individual i with experience t and γ is the Euler's constant.

Table 8 Panel A presents the value of accounting and other business education across worker type. This value corresponds to the expected life-time career value for workers with no prior work experience before they choose their jobs, i.e., for $t = 0$. The first row presents the distribution of workers' initial labor market endowment. Non-accounting majors are more common than accounting majors. Moreover, the first unobserved type (h), who perceives greater non-wage benefits of external accounting jobs, is more common than the second unobserved type. The second row presents the life-time career value conditional on worker types and accounting education. We find that the career value of a non-accounting major is about \$1.8 million, irrespective of their unobserved worker type. The career value of an accounting major of the first type ($h = 1$), which equals \$1.8 million, is similar in magnitude to that of non-accounting majors. In contrast, the career value of an accounting major of the second type ($h = 2$) is about \$42k lower than that of non-accounting major of the same type. The results suggest that the value of accounting education depends on unobserved worker type with some workers better suited for an accounting career than others. As the value of accounting education is lower for certain worker types, it may affect their ex-ante choice of business majors.

Table 8 Panel B presents the lifetime career values for workers with at least one-year work experience. The first column examines workers with prior external accounting experience, whereas the second examines workers without such an experience. We find that about 4% workers have external-accounting experience. Those with past external accounting experience earn higher wages on average at \$104k per year than those without it at \$87k per year. However, the expected value of past external accounting experience amounts to about \$1.5 million, compared to \$1.7 million for those without external accounting experience. As lifetime career value accounts for non-wage benefits, these results indicate a potential trade-off between higher wages and lower non-wage benefits associated with past external accounting experience.

5.5 Labor Demand

Table 9 Panel A reports the parameter estimates for labor demand. Recall that our model differentiates within- and across-sector competition for labor. On the one hand, we find that employers of sectors with many firms are less likely to internalize competition with other employers outside the sector than they do with employers of sectors with fewer firms ($\chi_1 > 0$). This leads to greater wage markdowns, as employers' labor market power stems from them internalizing the impact of wage changes on attracting talent. On the other hand, more firms in a sector increase competition for labor within that sector, reducing employers' market power ($\chi_2 > 0$).

Panel A also reports the rates of forced turnover, conditional on not making partner at Big 4 and Non-Big 4 accounting firms, which stand at an annual rate of 3.9% and 2.7%, respectively. These rates imply a maximum forced turnover rate of 72% ($=1-(1-0.039)^{32}$) and 58% ($=1-(1-0.027)^{32}$), respectively, over workers' life time (assuming 42 years of career with the first 10 years facing zero forced turnover rate).

Table 9 Panel B reports the sample average of $\nu_{i,k,t}$, the marginal product of labor. Among all sectors, the Finance & Consulting sector exhibits the highest average marginal product of labor, amounting to about \$111k. Big 4 accounting firms rank second with an average of \$100.99k, followed by technology firms at \$100.8k. Non-Big 4 Accounting and Internal Accounting jobs have the lowest marginal product of labor, at an average of \$86k and \$83k, respectively. The estimated marginal product of labor for accounting firms is comparable to the estimates in Banker et al. (2003).

Table 9 Panel C reports the average of wage markdowns, $\mu_{i,k,t}$, for each sector. Big 4 jobs have the highest wage markdowns \$3.14k. Finance/Consulting and Technology jobs have slightly lower wage markdowns, which equal to \$2.97 and \$2.84k, respectively. Internal accounting and non-Big 4 have lower markdowns at \$2.81k and \$2.66k, respectively.

5.6 Counterfactual Analysis

Our quantitative exercise seeks to understand employers' labor market power. To this end, we increase the wages offered in the external accounting, internal accounting, finance/consulting, and technology sectors to their competitive levels, that is, to each sector's marginal product of labor. Wages offered by other industries ($k = 6$) are held constant as we do not estimate its marginal product of labor. We then simulate how this change affects the labor market shares across these sectors. Since wages offered by other industries are held constant, all other sectors mechanically gain market shares. To remove this mechanical effect and isolate relative reallocation across the remaining five sectors (i.e., Big 4, non-Big 4, internal accounting, finance/consulting, and technology), we report percentage changes in labor market shares rescaled to these five sectors. That is, we normalize shares to sum to one among individuals choosing one of the five focal sectors in both the baseline and counterfactual scenarios.

Table 10 reveals that external accounting experiences the largest gain in market share, rising by 99.9%. This shift is driven by the relatively large wage markdowns imposed by Big 4 employers (see Table 9 Panel C), which are eliminated under the competitive wage scenario. Despite this gain, the share of internal accounting falls. Internal accounting becomes less attractive in the counterfactual due to its relatively low marginal product of labor, which makes it less attractive to workers compared to other sectors once wages reflect productivity. In terms a dynamic decision, those who start their careers at accounting firms and move to internal accounting positions at their later career might end up staying longer at accounting firms due to their competitive wages although non-wage benefits are lower.

6 Conclusion

This paper develops and estimates an equilibrium model of the accounting labor market, integrating both demand and supply factors in the analysis. In developing what we believe is the first such model, our theoretical approach incorporates and expands on the work of Keane and Wolpin (1997) and Sauer (1998) by incorporating accountants' forward-looking job choice decisions across six sectors. It also builds on the work of Lee and Wolpin (2006) and Berger et al. (2022) by considering those six sectors' productivity shocks and oligopsonistic employment decisions. Most importantly, our equilibrium model embraces the institutional features of accounting labor markets such as entry barriers (e.g., CPA certification and the 150-hour rule), partner promotion, (possible) technology shocks, and the oligopsony power of Big 4 firms (Barrios, 2022; Frecka et al., 2022; Maurer, 2023; Aobdia et al., 2024). Using individual-level data collected from multiple sources, we estimate the model to study business majors' dynamic occupation choices and their employers' oligopsonistic employment decisions.

Our quantitative model allows us to estimate unobservable parameters related to these specific features of the accounting labor market. The estimation results reveal that it is important to explicitly account for dynamic considerations when modeling workers' occupational choices, because dynamic considerations account for 98% of the variation in workers' return from their occupational choices. On the labor supply side, business majors face barriers to working for external accounting firms. On the labor demand side, although the wage markdowns of the Big 4 accounting sector are relative large, and their productivity lags behind. Making labor market competitive increases the supply of workers to external accounting firms but reduces the labor market share of internal accountants.

In closing, we want to offer some caveats concerning the application of our model and findings. First, while the counterfactual analyses help us understand economic forces that limit the supply of accountants to the economy, any concrete policy suggestions would require the modeling of specific policy frictions as well (e.g., frictions that give rise to the entry barriers faced by non-accounting majors). Policy makers should interpret our results in the context of our model assumptions and the findings in the literature. Second, although we incorporate several salient features of accounting labor markets, relying on prior studies and regulatory discussions (Schmalz, 2023), our focus and the curse of dimensionality force a trade-off on the features we include. This limitation naturally points to directions for future research. One such direction concerns the implications of STEM-designated accounting master's programs for international students as well as a general college major choice (Barrios et al., 2024). A second direction for future research is the various origins of the difference in the marginal product of labor across sectors (Goos et al., 2014; Friedman et al., 2024). A third direction could examine additional performance measures, as key performance measures are likely to vary across sectors. For example, a focus on audit quality, while limiting the focus to auditor labor markets, could yield additional insights about the auditor labor market (Breuer et al., 2023).

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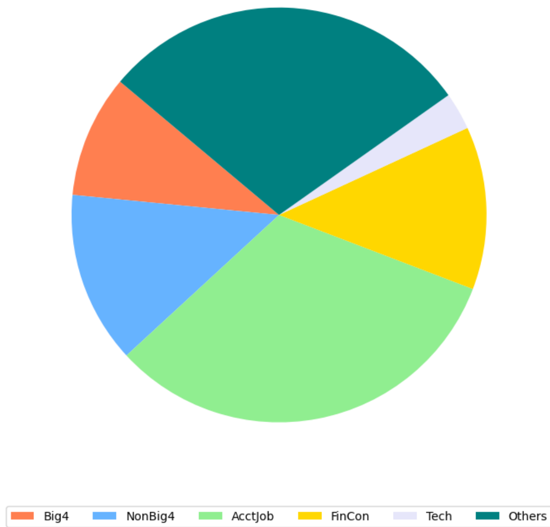
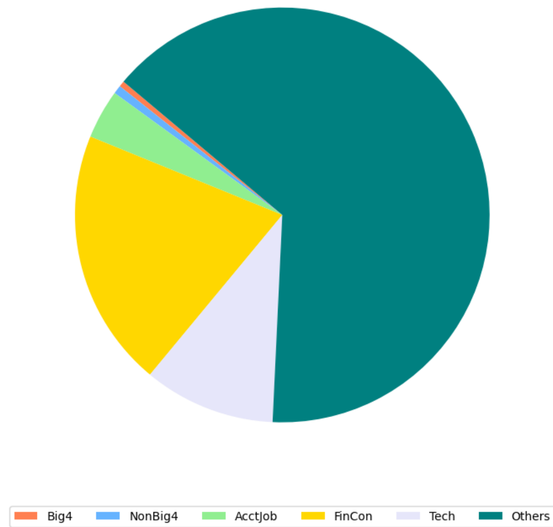
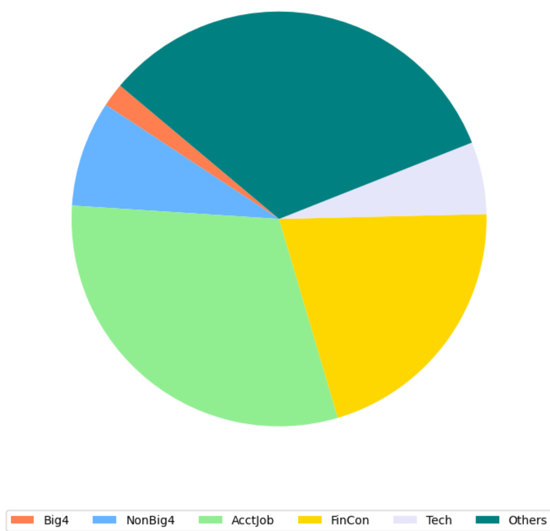
Figure 1: Career Distribution of Business Graduates



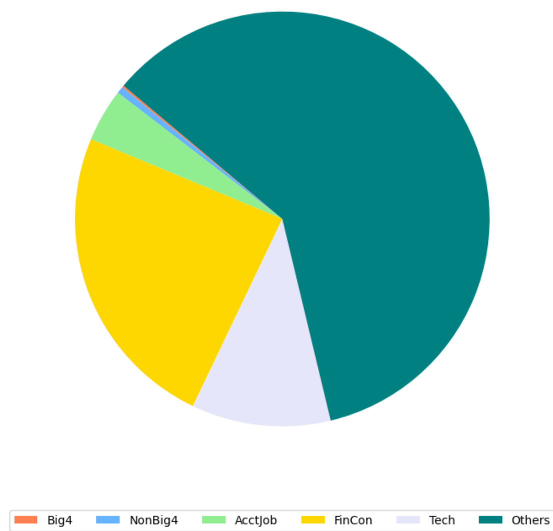
(a) Year 1 Proportion - Accounting Students



(b) Year 1 Proportion - Business Students



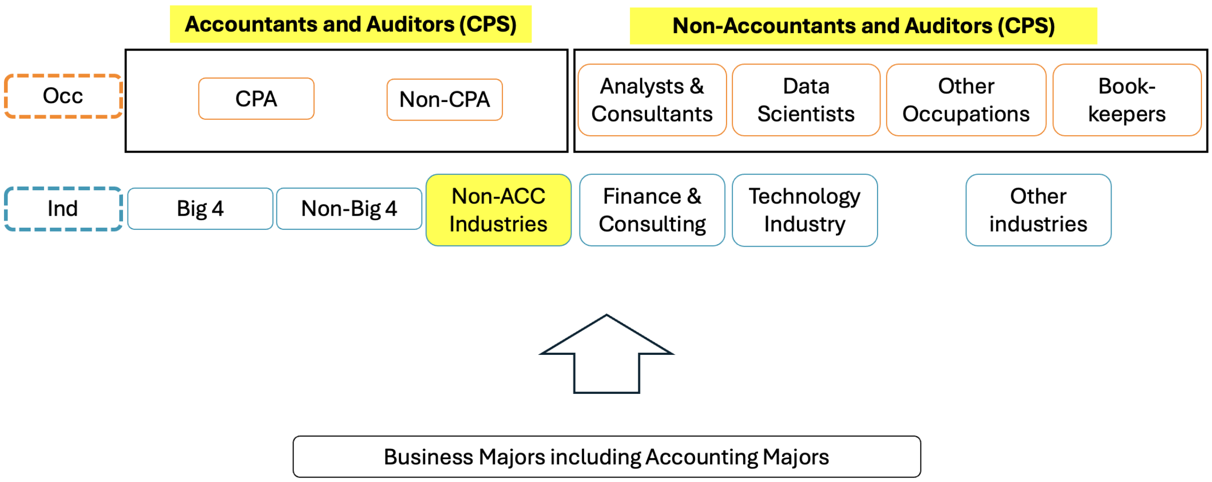
(c) Year 15+ Proportion - Accounting Students



(d) Year 15+ Proportion - Business Students

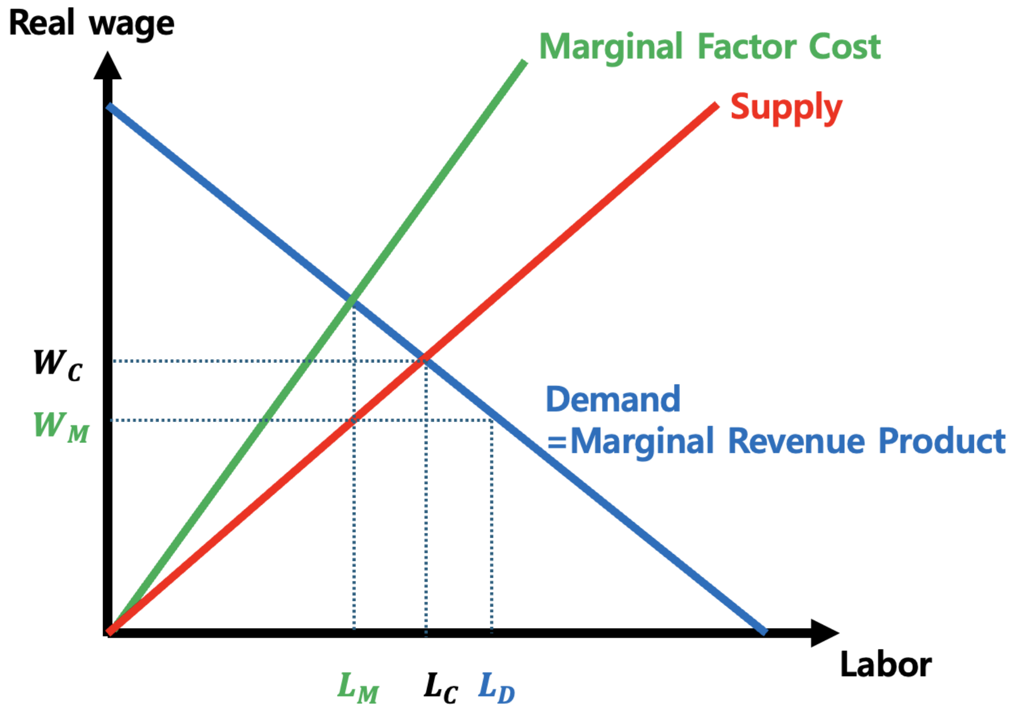
This figure shows the job category distribution for career positions held by business majors including accounting majors in the United States from 1 to 15 years(s) (inclusive) after graduation using Revelio data. Jobs held for over 15 years are collapsed under the distribution Year 15+. Career positions are separated into one of six categories based on the following criteria. 1) Big4: The position is labeled with an NAICS code beginning with 5412 (Accounting, tax preparation, bookkeeping, and payroll services), and job descriptions include accounting, accountant, audit, or financial reporting at one of the Big 4 accounting firms: Deloitte, PwC, EY, or KPMG. 2) NonBig4: The position is labeled with an NAICS code beginning with 5412, it is *not* at one of the Big 4 accounting firms, and job descriptions include accounting, accountant, audit, or financial reporting. 3) AcctJob: The position is not captured by categories 1 or 2 and has an aggregated role involving accounting. 4) FinCon: As a finance or consulting job at any firm, the position is labeled with an NAICS code beginning with 52 (Finance and Insurance) or 5416 (Management, Scientific, and Technical Consulting Services). 5) Technology: The position is labeled with an NAICS code beginning with 51 (Information), 5415 (Computer Systems Design and Related Services), or 5417 (Scientific Research and Development Services Techniques). 6) NonAcctJob: All other positions.

Figure 2: Sector Classification



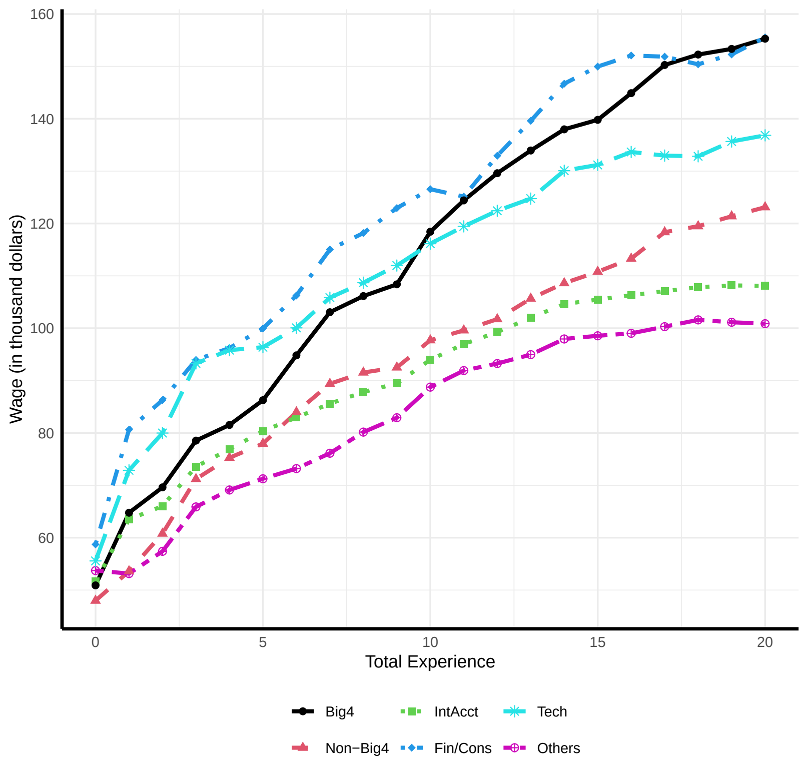
This figure depicts the sector classification. We use both occupation and industry to define each sector. For example, we define internal accountants as such because they work as an accountant or auditor in a non-accounting service industry.

Figure 3: Monopsony Power in the Labor Market



This figure describes the demand and supply of labor in the monopsonistic labor market. The equilibrium employment is determined by Marginal Labor Cost and Marginal Product of Labor. Under the equilibrium employment, the supply of labor determines the equilibrium wage and the employment gap between the demand and supply of labor.

Figure 4: Average Wages over Career of Business Majors



This figure plots the evolution of the wage profiles of Big 4 accounting firms (dots, solid line), non-Big 4 accounting firms (triangles, dashed line), Internal Accountant (squares, dotted line), Finance & Consulting (diamonds, dot-dash line), Technology (stars, long-dash line), and Others (circle-pluses, two-dash line) over workers' career.

Table 1: Demographics of External and Internal Accountants

Year	P/1000	Female	Education	Experience	Audit Firms	Mean Wage	Real Wage
1968	4.14	0.24	13.85	20.06	0.18	7,689.53	38,246.65
1973	4.91	0.25	14.57	18.99	0.16	11,403.26	45,063.68
1978	9.07	0.35	15.00	16.85	0.19	14,540.65	39,587.52
1983	10.13	0.39	15.20	16.74	0.22	22,014.92	37,801.69
1988	10.46	0.51	15.29	15.85	0.19	28,067.98	41,176.26
1993	11.41	0.52	15.39	17.20	0.19	32,058.47	38,060.13
1998	11.50	0.60	15.33	17.59	0.17	36,830.92	37,832.74
2003	12.97	0.59	15.69	20.19	0.18	48,130.98	44,374.12
2008	12.55	0.63	15.69	19.97	0.22	56,453.97	45,389.62
2013	12.61	0.65	15.91	21.71	0.23	62,708.66	45,873.19
2014	12.82	0.65	15.79	22.26	0.22	61,757.00	44,452.95
2015	11.65	0.58	15.79	22.63	0.25	62,992.80	44,662.50
2016	11.83	0.63	15.73	23.30	0.24	63,219.06	44,686.80
2017	11.50	0.59	15.90	22.49	0.27	69,286.91	48,735.57
2018	12.27	0.61	15.96	21.78	0.21	68,368.99	46,912.62
2019	12.63	0.64	15.91	22.12	0.27	67,567.45	45,364.83
2020	11.71	0.61	16.12	22.27	0.22	74,788.11	49,663.37
2021	11.12	0.59	16.18	21.62	0.27	74,514.25	48,396.05
2022	10.75	0.62	16.23	21.48	0.27	79,727.52	49,638.76
2023	10.05	0.59	16.21	21.33	0.29	83,035.69	48,997.38

The table describes the demographics of accountants. The data are sourced from the Current Population Survey. P/1000 represents the number of accountants per 1000 individuals in the workforce. Female denotes the percentage of accountants who are female. Education refers to the average years of education among accountants. Experience indicates the average years of experience in the industry. Audit Firms represents the percentage of accountants working in audit firms. Mean Wage represents the average wage of accountants in the workforce. Real Wage inflates or deflates dollar amounts of Mean Wage to the amount they would have represented in 1999 using CPI.

Table 2: Degrees in Accounting Awarded

Year	Bachelor's	Master's	Accounting Major
1980	43,344	3,449	46,793
1982	45,732	3,046	48,778
1984	47,005	3,207	50,212
1986	43,813	2,920	46,733
1988	43,990	3,265	47,255
1990	45,610	3,566	49,176
1992	48,853	3,887	52,740
1994	43,940	4,494	48,434
1996	40,377	4,424	44,801
1998	37,362	4,789	42,151
2000	32,672	5,295	37,967
2002	33,502	6,830	40,332
2004	37,722	9,085	46,807
2006	41,964	10,415	52,379
2008	44,514	11,415	55,929
2010	48,390	15,937	64,327
2012	49,362	17,587	66,949
2014	50,510	19,261	69,771
2016	50,688	19,468	70,156
2018	48,790	18,980	67,770
2020	46,463	16,490	62,953

This table shows the number of college and graduate students awarded degrees in accounting. We use data from the US Department of Education (NCES) and Integrated Postsecondary Education Data System (IPEDS).

Table 3: Financial Data for Big 4 and Non-Big 4 Accounting Firms

	Revenue	
Year	Big4	Non-Big4
2010	7,697	123
2011	7,740	121
2012	8,411	127
2013	9,143	134
2014	10,044	143
2015	10,851	155
2016	11,857	169
2017	13,317	187
2018	14,033	201
2019	14,689	217
2020	16,071	239
2021	16,637	251
2022	16,761	286
2023	19,804	341
2024	22,270	386
Avg	13,288	205

The table describes the industry and organizational structure of 100 accounting firms from 2010 to 2024. The data are sourced from Accounting Today's survey. Each number is the average at the group (i.e., Big4, Non-Big4).

Table 4: Wage Regression with Accounting and Non-Accounting Sectors

	(1)	(2)
	1968-2023	2009-2023
Experience	0.0891***	0.0808***
	(0.0014)	(0.0018)
Experience Squared	-0.00151***	-0.00134***
	(0.0000)	(0.0000)
Nonwhite	-0.0717***	-0.0692***
	(0.0035)	(0.0037)
Marital Status	0.208***	0.227***
	(0.0040)	(0.0023)
Years of Education	0.127***	0.127***
	(0.0006)	(0.0009)
Female	-0.486***	-0.423***
	(0.0104)	(0.0058)
Accounting Sector	0.254***	0.279***
	(0.0082)	(0.0118)
Female × Accounting Sector	0.168***	0.100***
	(0.0171)	(0.0185)
Finance Sector	0.468***	0.472***
	(0.0047)	(0.0073)
Technology Sector	0.397***	0.417***
	(0.0059)	(0.0091)
Firm Size	0.0508***	0.0445***
	(0.0019)	(0.0012)
Constant	7.119***	7.446***
	(0.0183)	(0.0346)
Year Fixed Effects	Yes	Yes
Mean of Dependent Var.	9.961	10.290
R-squared	0.393	0.334
Adjusted R-squared	0.393	0.334
Observations	3,061,313	1,307,454

This table describes the wage regression. The data are sourced from CPS. Experience indicates the years of experience in the industry. Female, Non-white, and Marital are indicator variables. Education refers to the years of education (e.g., 12, 16, and so on). Accounting, Finance, and Technology Sectors are indicator variables based on individuals' occupations and employers. Firm size is measured as a categorical variable. The model includes experience, gender, race, marital status, education, occupation, firm size, and other relevant factors as explanatory variables. The sample consists of 3,061,313 observations from 1968 to 2023. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the year level. Standard errors are shown in parentheses.

Table 5: Summary Statistics

Variables	N	Mean	SD	1%	25%	50%	75%	99%
$k = 1$	10,940,852	0.006	0.077	0.000	0.000	0.000	0.000	0.000
$k = 2$	10,940,852	0.012	0.109	0.000	0.000	0.000	0.000	1.000
$k = 3$	10,940,852	0.062	0.241	0.000	0.000	0.000	0.000	1.000
$k = 4$	10,940,852	0.194	0.395	0.000	0.000	0.000	0.000	1.000
$k = 5$	10,940,852	0.098	0.297	0.000	0.000	0.000	0.000	1.000
$k = 6$	10,940,852	0.628	0.483	0.000	0.000	1.000	1.000	1.000
m^b	10,940,852	0.000	0.007	0.000	0.000	0.000	0.000	0.000
m^{nb}	10,940,852	0.000	0.014	0.000	0.000	0.000	0.000	0.000
non_acc	10,940,852	0.915	0.280	0.000	1.000	1.000	1.000	1.000
t	10,940,852	8.236	5.570	0.000	4.000	8.000	12.000	20.000
w	10,940,852	89.557	34.487	39.283	63.678	83.475	105.116	196.858
x	10,940,852	6.780	5.269	0.000	2.000	6.000	10.000	20.000

This table presents the summary statistics of key variables from the Revelio data: $female$ is an indicator that equals one for females and zero otherwise; k=$l \in \{1, ..., 6\}$ is an indicator for choosing job sector l; m^b indicates whether the individual works in a manager position for a Big 4 accounting firm; m^{nb} indicates whether the individual works in a manager position for a non-Big 4 accounting firm; non_acc is an indicator that equals one if a worker does *not* hold an accounting degree and zero otherwise; t represents total experience since the start of a worker's first job; w represents wages in thousand dollars; and x represents a worker's experience in their current job sector.

Table 6: Value Function Decomposition and Model Fit

Panel A: Decomposition of Choice-Specific Value Functions

	Per-Period Return	Expected Future Payoff
Variance	2.164%	97.836%

Panel B: Model Fit

	Big4	NonBig4	AcctJob	FinCon	Tech	Others
Original	0.9%	1.1%	6.8%	20.0%	9.6%	61.7%
Estimated	0.9%	1.1%	6.7%	19.9%	9.5%	61.9%

Panel A of this table decomposes the total *variance* of workers' choice-specific value functions into the current-period utility (column (1)) and expected future utility (column (2)). Panel B reports the model fit.

Table 7: Parameter Estimates for Labor Supply

Panel A: Parameter Estimates of Non-Wage Benefits								
$\alpha_1 - \alpha_4$	$\alpha_2 - \alpha_4$	$\alpha_3 - \alpha_4$	$\alpha_5 - \alpha_4$	γ_1	λ_1	ψ_1	ψ_2	θ
−52.347***	−23.872***	−12.314***	−10.495***	−17.943***	−70.910***	−45.683***	−0.181***	0.015***
(0.499)	(0.493)	(0.167)	(0.000)	(0.333)	(0.535)	(0.276)	(0.026)	(0.000)

Panel B: Parameter Estimates of Structural State Dependence						
ξ_0	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6
94.854***	23.509***	22.249***	21.813***	16.161***	18.705***	11.091***
(0.331)	(0.109)	(0.097)	(0.071)	(0.058)	(0.065)	(0.039)

This table presents the parameter estimates for the dynamic career choice model presented in Section 3. Individuals choose among K job options, which include Accountants in Big 4 (k=1), Accountants in Non-Big 4 (k=2), Accountants in Other Industries (k=3), Finance & Consulting (k=4), Technology (k=5), and Non-Accounting in Other Industries (k=6). The current-period return from choosing job k for individual i with a total number of years of work experience t equals:

$$U_{i,k,t} = w_{i,k,t} + b_{i,k,t} + \xi_{i,j,k,t} + \theta^{-1}\epsilon_{i,k,t},$$

where $w_{i,k,t}$ represents the wage of choosing job k; $b_{i,k,t}$ represents the non-wage benefits/costs of choosing job k; $\xi_{i,k,t}$ denotes the benefits of continuing the prior job; j_{it} indicates individual i's prior-year job; and $\epsilon_{i,k,t}$ is job-specific taste shock, which follows a standard Type I extreme value distribution. Non-wage benefits are linear in the state variables:

$$\begin{aligned} b_k(\mathbf{s}_{i,t}) = &\sum_{l=1}^{5}\Big(\alpha_l \mathbb{1}\{k=l\}\Big) + \gamma_1 non\_acc_i \mathbb{1}\{k \le 2\} + \lambda_1 \mathbb{1}\{h_i = 2\}\mathbb{1}\{k \le 2\} \\ &+ (\psi_1 ext\_acc_{i,t} + \psi_2 ext\_acc_{i,t} \times t)\mathbb{1}\{k \ge 3\}, \end{aligned}$$

where non_acc_i is an indicator variable that equals one if individual i does *not* hold an accounting degree and zero if they do; and $ext\_acc_{i,t}$ is an indicator equal to one if individual i worked for external accounting firms in the past, and zero if they did not. The benefits of continuing the prior job for individual i equal

$$\xi_{i,j,k,t} = \sum_{l=1}^{6}\left(\mathbb{1}\{k_{i,t} = j_{i,t} = l\} \times \mathbb{1}\{j_{i,t} \neq 0\}\Big(\xi_0 \mathbb{1}\{x_{i,k,t} \le 2\} + \xi_l x_{i,k,t}\Big)\right),$$

where $x_{i,j,t}$ is the experience in sector j for individual i with a total experience t prior to choosing jobs. Standard errors are presented below coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Table 8: The Value of Accounting Education and External Accounting Experience

Panel A: The Value of Accounting Education

	Accounting Major		Other Business Majors	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Probability	0.061	0.025	0.688	0.226
Ex-ante Value (in million \$)	1.811	1.790	1.835	1.832

Panel B: The Value of External Accounting Experience

	With External Accounting Experience	Without External Accounting Experience
Probability	0.040	0.960
Annual wages (in thousand \$)	103.605	86.333
Ex-ante Value (in million \$)	1.499	1.725

This table estimates the value of accounting. Panel A reports the value of accounting education. The first row reports the distribution of workers by worker type and major. The second row presents the discounted lifetime career value (in million dollars) of obtaining an accounting major or other business majors for individuals of type $h \in \{1, 2\}$ with *no prior work experience*. Specifically, the value is given by:

$$\log\left(\sum_{k=1}^{6} e^{V_{i,k,0}} + \theta^{-1}\gamma\right),$$

where $V_{i,k,0}$ denotes the choice-specific value function for occupation k and individual i at the entry stage (with no prior job experience), and γ is Euler's constant. Panel B reports the average value of past experience in external accounting jobs among workers *with work experience of at least one year*. The first row reports the proportion of individuals who either have or do not have an external accounting experience among those who have at least one-year work experience. The second row reports the average annual wage for these individuals. The third row presents the average discounted lifetime career value (in million dollars) among these individuals. Specifically, the value is given by:

$$\log\left(\sum_{k=1}^{6} e^{V_{i,k,t}} + \theta^{-1}\gamma\right),$$

where $t \geq 1$.

Table 9: Parameter Estimates for Labor Demand

Panel A: Parameter Estimates

Oligopsony			Forced Turnover	
χ_1	χ_2		ζ_b	ζ_{nb}
0.108**	0.320***		0.039***	0.027***
(0.045)	(0.002)		(0.001)	(0.001)

Panel B: Marginal Product of Labor

$\bar{\nu}_1$	$\bar{\nu}_2$	$\bar{\nu}_3$	$\bar{\nu}_4$	$\bar{\nu}_5$
100.991***	86.612***	83.105***	111.155***	100.842***
(0.083)	(0.058)	(0.025)	(0.016)	(0.022)

Panel C: Wage Markdown

$\bar{\mu}_1$	$\bar{\mu}_2$	$\bar{\mu}_3$	$\bar{\mu}_4$	$\bar{\mu}_5$
3.138***	2.658***	2.809***	2.970***	2.837***
(0.004)	(0.003)	(0.001)	(0.000)	(0.001)

This table presents the average marginal product of labor and the percentage of wage markdown at the sector level. The wage offer of a representative firm in sector k equals

$$w_{i,k,t} = \nu_{i,k,t} \underbrace{\frac{1}{\frac{\sum_{h=1}^{H} \pi_h \hat{\eta}_{i,k,t}^{(h)}(1-\hat{\eta}_{i,k,t}^{(h)})}{\hat{\eta}_{i,k,t}} \theta e^{-\chi_1 (M_{i,k,t}-1)} + \frac{M_{i,k,t}-1}{M_{i,k,t}} * \chi_2}}_{\equiv \mu_{i,k,t}},$$

where $\nu_{i,k,t}$ is the marginal product of labor of sector k of employees with characteristics $\mathbf{s}_{i,t}$; $\mu_{i,k,t}$ is the wage markdown; $\hat{\eta}_{i,k,t}$ is the demand for individuals with characteristics $\mathbf{s}_{it}$ from Sector k (defined in Section 3.1), expressed as a fraction of the total number of workers with the same characteristics; and $M_{i,k,t}$ is the number of employers (firms) in Sector k hiring individuals with characteristics $\mathbf{s}_{it}$. Panel A reports parameters for labor demand and the *annual* rate of forced turnover conditional on not making partner in the prior year. Panel B reports the average $\nu_{i,k,t}$ by sector. Panel C reports the average wage markdown by sector. Standard errors are presented below coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

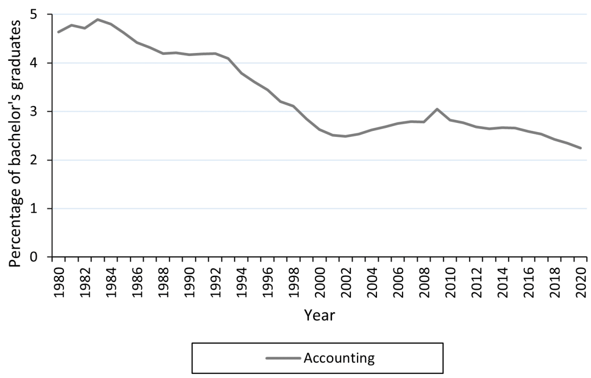
Table 10: Counterfactual Analyses of Competitive Labor Markets

	External Accounting (1)	Internal Accounting (2)	External + Internal (3)	FinCon/Tech (4)
% Change in Employment	99.85%	-6.29%	13.82%	-4.61%

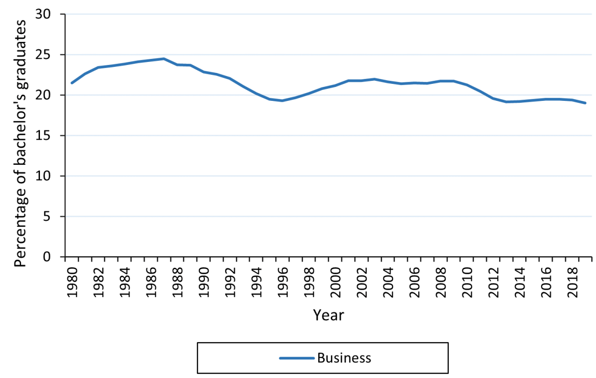
This table conducts a counterfactual analysis to understand the effect of employers' labor market power on the supply of accountants. We first compute labor demand by setting the wages offered by Big 4, non-Big 4, internal accounting, finance/consulting, and technology sectors to their competitive labor market levels, which equal their marginal product of labor. Wages offered by other industries ($k = 6$) are held constant as we do not estimate their marginal product of labor. We then evaluate how this change affects the labor market shares across the remaining five sectors. To isolate relative labor reallocation across these five sectors (i.e., Big 4, non-Big 4, internal accounting, finance/consulting, and technology), we report percentage changes in labor market shares rescaled to these five sectors. That is, we normalize labor market shares to sum to one among individuals choosing one of the five focal sectors in both the baseline and counterfactual scenarios.

Online Appendix

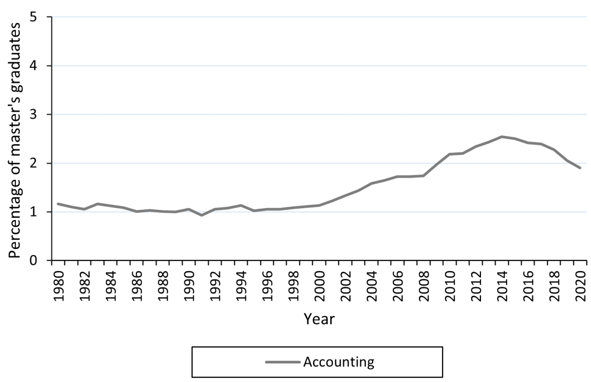
Figure OA1: College and Graduate Major Choice



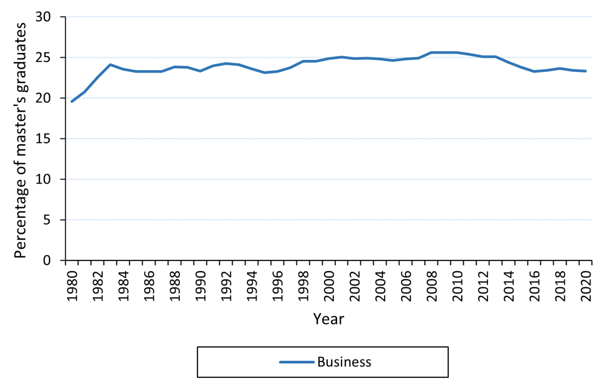
(a) Bachelor's Degrees - Accounting Students



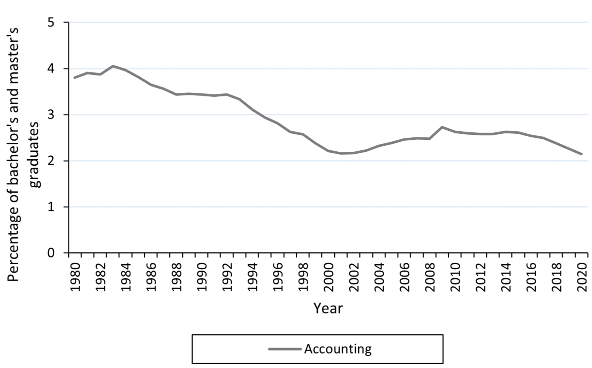
(b) Bachelor's Degrees - Business Students



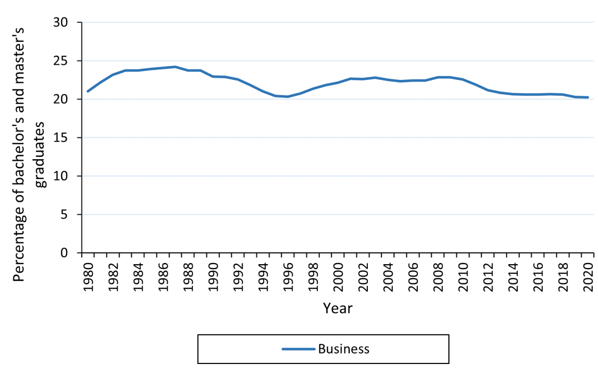
(c) Master's Degrees - Accounting Students



(d) Master's Degrees - Business Students



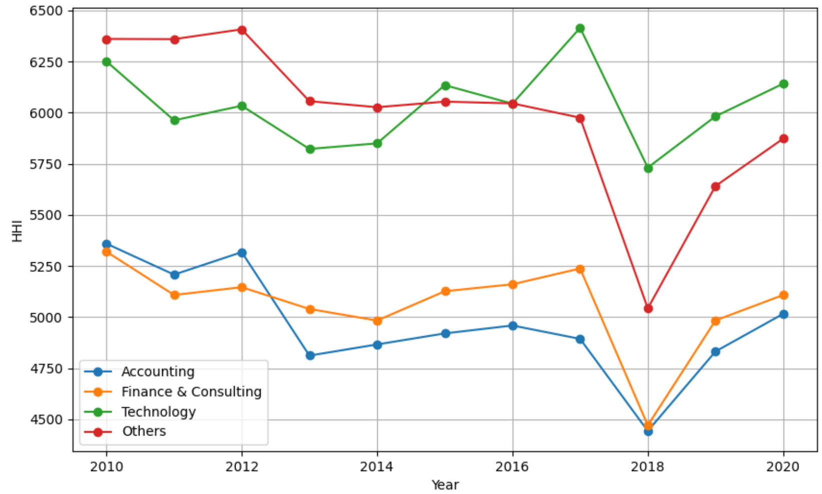
(e) Combined Degrees - Accounting Students



(f) Combined Degrees - Business Students

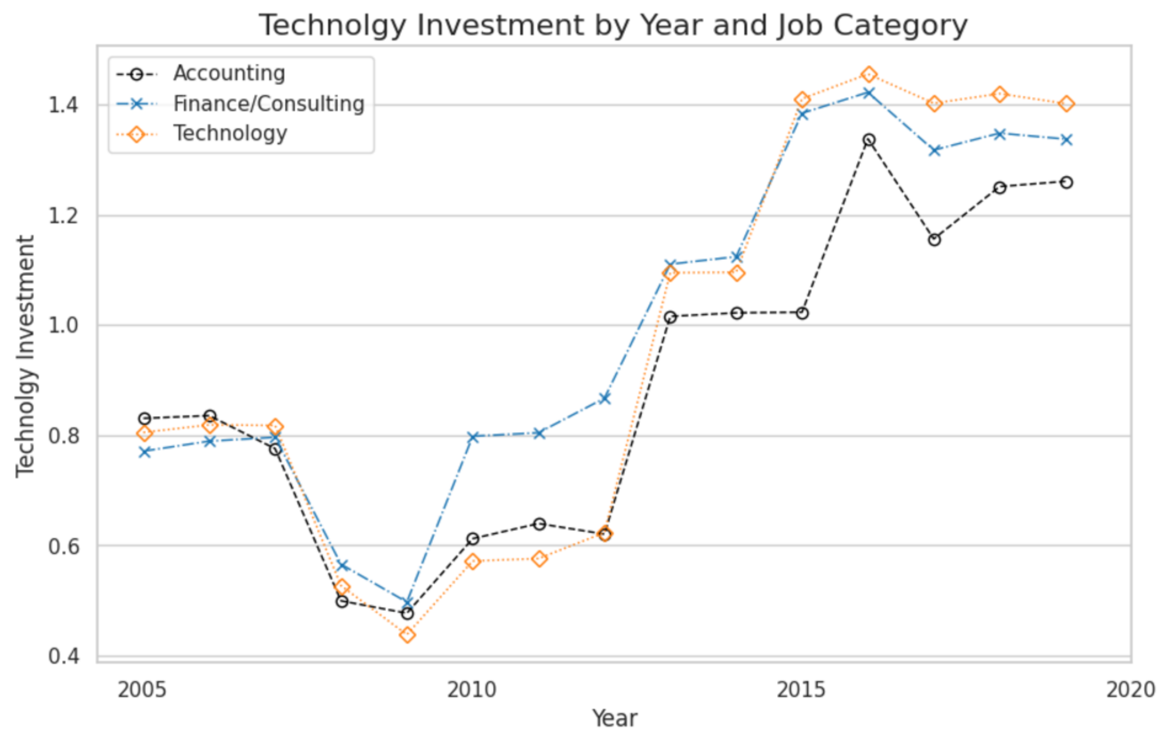
This figure shows the annual trend of the percentage of postgraduate degrees in Business and Accounting for all postgraduate students. We use data from the US Department of Education (NCES) and the Integrated Postsecondary Education Data System (IPEDS). The data system provides detailed information on degrees conferred by postsecondary institutions for each field of study. Panel (a) and (b) plot the annual trend in the percentage of bachelor's degrees. Panel (c) and (d) plot the annual trend in the percentage of master's degrees. Panel (e) and (f) plot the annual trend in the percentage of combined bachelor's and master's degrees.

Figure OA2: Occupational HHI Trends over Time



This figure shows the average Herfindahl-Hirschman Index (HHI) trends for three occupational categories—accountants, financial & consulting occupations, technical occupations, and all other occupations—over the years 2010 to 2020. The HHI is first calculated at the county-year-occupation level and then averaged at the year level for each occupational category.

Figure OA3: Technology Investment by Year and Job Category



This figure depicts the technology investment by year and by job category. The technology investment is measured by the number of computers per each employee using the CiTDB dataset.

Table OA1: Demographics of Lawyers

Year	P/1000	Female	Education	Experience	Law Firms	Mean Wage	Real Wage
1968	1.48	0.03	17.18	20.97	0.60	14,378	65,288
1973	2.29	0.09	17.28	14.96	0.53	13,246	49,738
1978	3.34	0.12	17.67	12.59	0.42	22,283	57,308
1983	3.90	0.17	17.73	13.72	0.34	38,514	64,464
1988	4.59	0.23	17.68	14.36	0.35	48,492	68,268
1993	4.41	0.29	18.15	16.48	0.32	63,184	72,875
1998	5.08	0.31	18.56	18.24	0.34	96,882	99,063
2003	4.89	0.33	18.75	19.35	0.30	123,610	111,971
2008	5.46	0.35	18.67	19.91	0.33	142,885	110,504
2013	6.74	0.35	18.91	21.47	0.37	156,428	111,948
2018	7.32	0.39	18.98	20.83	0.40	154,614	103,382
2023	7.52	0.46	18.72	21.60	0.43	200,435	124,119

This table describes the demographics of lawyers. The data are sourced from the Current Population Survey. P/1000 represents the number of lawyers per 1000 individuals in the workforce. Female denotes the percentage of lawyers who are female. Education refers to the average years of education among lawyers. Experience indicates the average years of experience in the industry. Law Firms represents the percentage of lawyers working in law firms. Mean Wage represents the average wage of lawyers in the workforce. Real Wage inflates or deflates dollar amounts of Mean Wage to the amount they would have represented in 1999 using CPI.

Table OA2: Partner Promotion

Year	Count(Male)	Count(Female)	Promotion(Male)	Promotion(Female)	Avg. Year
1993	178	117	0.034	0.026	7.136
1994	189	129	0.021	0.023	7.588
1995	196	128	0.031	0.008	9.514
1996	207	162	0.039	0.025	8.935
1997	245	199	0.045	0.010	6.196
1998	254	250	0.028	0.004	7.140
1999	280	287	0.025	0.017	7.098
2000	361	323	0.030	0.009	8.377
2001	332	339	0.024	0.015	9.306
2002	376	379	0.027	0.016	11.111
2003	471	454	0.036	0.015	12.727
2004	568	560	0.023	0.023	10.519
2005	765	754	0.021	0.012	8.954
2006	814	827	0.018	0.004	9.018
2007	1056	901	0.016	0.004	11.548
2008	975	922	0.010	0.007	10.840
2009	822	751	0.012	0.003	9.250
2010	853	742	0.011	0.003	10.294

This table describes the partner promotion probability for each junior accountant cohort by gender from 1993 to 2010 considering the average years to become a partner at accounting firms.

Table OA3: List of Industries for Accounting Graduates

Industry Name (NAICS)	N	Proportion
Professional, Scientific, and Technical Services (54)	112,739	0.293
Finance and Insurance (52)	65,179	0.169
Manufacturing (33)	27,449	0.071
Educational Services (61)	22,495	0.0585
Information Technology (51)	21,668	0.0563
Public Administration (92)	14,683	0.0382
Retail Trade (45)	13,779	0.0358
Manufacturing (32)	13,497	0.0351
Health Care and Social Assistance (62)	11,009	0.0286
Accommodation and Food Services (72)	10,489	0.0273
Total	384,719	1

This table provides descriptive statistics on the top 10 industries with the most significant frequencies of jobs held by accounting majors. The industries are classified under NAICS and identified by the company where workers' positions are held. The table showcases raw and relative frequencies of the NAICS code's prevalence in Revelio's LinkedIn career path dataset filtered for accounting majors. Since NAICS employs a hierarchical structure, we use 2-digit codes to aggregate the dataset at the sector level, which comprises 20 total unique classifications.

Table OA4: List of Occupations for Accounting Graduates

Occupation	N	
Accountant	212,491	0.552
Billing Specialist	26,024	0.0676
Financial Advisor	16,250	0.0422
Investment Specialist	12,375	0.0322
Coordinator	12,209	0.0317
Cashier	11,427	0.0297
Crew Member	10,919	0.0284
Data Analyst	5,561	0.0145
Legal	5,303	0.0138
Customer Service	4,752	0.0124

This table describes the distribution of accounting majors' work positions/roles 5 years post-graduation. The position roles are aggregated at 50 discrete levels based on Revelio's clustering algorithm, which starts with millions of unique job titles scraped from LinkedIn profiles and iteratively clustered to create increasingly broad occupational groups. This produces the k50 identification, a set of the 50 most representative titles for the cumulative collection of LinkedIn job titles. We utilize this k50 identification to aggregate accounting majors' job titles for positions held 5 years after the completion of their degree.

Table OA5: College Majors in Accounting Firms

Field	N
Business	423,294
Accounting	336,335
Engineering	97,629
Finance	83,504
Economics	53,787
Law	15,483
Mathematics	10,764
Marketing	9,719
Education	9,667
Information Technology	5,717

This table provides descriptive statistics for the raw frequency distribution of college majors of individuals working and/or previously employed at a Big 4 accounting firm (PwC, Deloitte, EY, and KPMG). We filter the Revelio dataset for all records of Big 4 employment, which includes all post-secondary degree levels from associate's to doctoral degrees. We then construct this table by aggregating counts of distinct combinations of userid (unique identifier for users) and degree level (i.e., bachelor's, master's) for every row classified by college major field. Users may be double-counted due to the Cartesian Product effect of cross-joining positions and education entries, which augments the total record count. Individuals will be counted multiple times in the same row if 1) the individual held multiple positions at one or more Big 4 firms, and 2) the individual has multiple degrees in the same field at different levels. Individuals will be double-counted in different rows if the individual has multiple degrees in different fields.

Table OA6: University Graduates in Accounting Firms

University Name	N
Gies College of Business, University of Illinois Urbana-Champaign	10,355
University of Southern California	9,699
New York University	9,325
Red McCombs School of Business, University of Texas at Austin	8,489
College of Business Administration, University of Central Florida	7,106
Stephen M. Ross School of Business, University of Michigan	6,539
Columbia University in the City of New York	6,275
George Washington University	5,907
Pennsylvania State University	5,195
Kelley School of Business, Indiana University	5,180

This table provides the raw frequency count for the universities of Big 4 accounting firms' current and past employees. Each row counts the distinct number of userids (unique user identifiers), degree levels, and positionids (unique job position identifiers) for the corresponding university identified in the University Name column. Users may be double-counted in one row if they have multiple degrees (e.g., bachelor's and master's) from the same institution. The initial dataset contained different naming conventions for the same university. We combined counts for institutions based on keyword matches that exceeded the threshold of 75% (more than 75% of the keywords in the first university name matched the keywords in a second university name).