Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition*

Tania Babina† Anastassia Fedyk‡

Alex He§ James Hodson¶

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Abstract

We study the shifts in U.S. firms' workforce composition and organization associated with the use of AI technologies. To do so, we leverage a unique combination of worker resume and job postings datasets to measure firm-level AI investments and workforce composition variables, such as educational attainment, specialization, and hierarchy. We document that firms with higher initial shares of highly-educated workers and STEM workers invest more in AI. As firms invest in AI, they tend to transition to more educated workforces, with higher shares of workers with undergraduate and graduate degrees, and more specialization in STEM fields and IT and analysis skills. Furthermore, AI investments are associated with a flattening of the firms' hierarchical structure, with significant increases in the share of workers at the junior level and decreases in shares of workers in middle-management and senior roles. Overall, our results highlight that adoption of AI technologies is associated with significant reorganization of firms' workforces.

Keywords: artificial intelligence, technological change, technology adoption, human capital, workforce composition, firm organization

JEL codes: D22, E22, J23, J24

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†Columbia University. Email: tania.babina@gsb.columbia.edu.

‡University of California, Berkeley. Email: fedyk@berkeley.edu.

§University of Maryland. Email: axhe@umd.edu.

¶Cognism; AI for Good Foundation. Email: hodson@ai4good.org.

The arrival of new general purpose technologies (GPT) is a key driver of economic growth (Romer, 1990; Aghion and Howitt, 1992). Yet as firms adapt their production processes and organization in response to technological changes, this shift raises major concerns about the impact on workers. For example, computer software and robots have displaced low- and medium-skilled workers (Autor et al., 2003; Acemoglu and Restrepo, 2020), while the arrival of the cotton-spinning machinery and electricity led to a complete re-organization of production processes within firms (Fizsbein et al., 2020; Juhász et al., 2020). In recent years, the focus has shifted to a new technological wave: artificial intelligence and related "big data" technologies. AI is a prediction technology, and predictions are at the heart of decision-making under uncertainty (Agrawal et al., 2019), making AI applicable to solve a variety of business problems with opposing potential effects on labor. On the one hand, firms might use AI to automate certain tasks, displacing labor and contributing to the ongoing trends of deskilling (Acemoglu et al., 2021). On the other hand, investments in AI so far have been primarily associated with product innovation (Babina et al., 2021), which can require complementary investments and more educated workforces. Indeed, Babina et al. (2021) document that AI-investing firms actually experience increases in their overall employment—and it is an open question whether this employment growth is associated with changes in labor composition, and how.

In this paper, we examine whether firms that invest more heavily in AI technologies experience changes in labor composition and workforce organization. To date, in-depth empirical understanding of the relationship between firms' investments in new AI technologies and firms' labor composition has remained elusive due to two key challenges: the difficulty of measuring firm-level AI investments and the lack of granular data on firms' labor composition and labor organization (Seamans and Raj, 2018; Frank et al., 2019). Several recent papers made progress in overcoming the first challenge by using firms' job postings and resumes to identify the hiring and stock of AI-skilled labor (Acemoglu et al., 2020; Babina et al., 2021; Alekseeva et al., 2020; Abis and Veldkamp, 2020). The main contribution of this paper lies in overcoming the second challenge: we use matched employer-employee U.S. data based on worker resumes, including detailed information on both individual jobs and employees' backgrounds, to construct firm-level measures of labor composition and workforce organization, including employees' educational backgrounds and hierarchical positions, and link them to firm-level AI investments measured in the same dataset. We find that firms that invest more in AI significantly shift towards more educated workforces, with greater emphasis on STEM degrees and skills in data analysis and IT. At the same time, AI-investing firms become less top-heavy in terms of their organizational structure, with increasing shares of junior employees and less emphasis on middle-management and senior roles. Overall, our findings suggest that investments in AI are associated with major changes in firms' labor composition and organization, translating into a broader shift towards more junior employees with high educational attainment and technical expertise.

In order to construct workforce composition measures and assess their relationships to firms' AI investments, we leverage a unique combination of datasets that capture both the *stock* of current employees and the *demand* for new employees among U.S. firms. The stock of current employees at each point in time comes from a resume dataset provided by Cognism Inc, which offers job histories for 535 million individuals globally. Cognism resume data offer a complementary perspective to granular administrative firm-worker matched U.S. data, which contain individual workers' wages but do not feature comprehensive information on individual workers' educational backgrounds or job characteristics. Cognism resume data, while representing more than 64% of full-time U.S. employment as of 2018, offer detailed job titles and descriptions (from which Cognism infers hierarchical positions) and educational backgrounds including degree-granting institutions and majors. We complement the resume data with information on firms' demand for new workers from the job postings data provided by Burning Glass, which capture 180 million online job vacancies. While job postings data have been instrumental in understanding how firms target their new hiring, the resume data provide a full picture of what happens to the overall workforce within firms—including new hires and potential displacement. Since our goal is to study the impact of AI on AI-using firms rather than AI-producing firms, we exclude firms in the tech sectors, which are likely to be producers of new AI tools.

We begin our analysis by describing how firm ex-ante labor composition predicts future growth in firms' AI investments. We adopt the novel measure of AI investments proposed by Babina et al. (2021), based on firms' AI-skilled human capital. The human-capital-based approach is motivated by the heavy reliance of AI implementation on human expertise. This method first identifies skills that are empirically related to principal AI technologies (machine learning, computer vision, and natural language processing) from the Burning Glass job postings data and then uses the identified highly AI-related skills to classify AI-related workers in the Cognism resume data. At the firm level, growth in AI investments is more pronounced among firms that initially have more workers with doctoral degrees and STEM majors. This is in line with the evidence in Babina et al. (2021), who find that firms with more workers in fields related to AI and more educated workers are able to attract AI talent more easily. The hierarchical structure of the firms' labor organization—as measured by the shares of employees in junior, middle-management, and senior roles—does not significantly predict growth in AI investments.

We next address our main question: whether AI investments are associated with changes in labor composition and workforce organization. We consider three sets of outcomes related to firms' workforce composition and organization. First, motivated by the literature on technologies and firm organization (Acemoglu et al., 2007), we examine changes in firms' organizational structure using measures of the hierarchical structure from the resume data. The relationship between technological investments and the relative weights of different hierarchical levels is ex ante ambiguous. As highlighted by theoretical work (Garicano and Rossi-Hansberg, 2006; Bloom et al., 2014), different types of technologies can have opposing effects on the need for managerial layers. Second, we look at both workers' education levels in the resume data and educational requirements in the job postings data to test whether AI facilitates skill-biased technological change (Autor et al., 1998; Machin and Van Reenen, 1998) or replaces high-skilled labor as predicted by Webb (2020). Here, too, the predicted effect of AI is ex ante ambiguous, and we provide the first systematic evidence of its direction. The shifts in labor composition are likely to go hand-in-hand with changes to organizational hierarchies, as Caroli and Van Reenen (2001) point out that flatter hierarchical structures require higher human capital from each individual employee. Finally, we use detailed information on workers' majors and required skills to study how AI changes firms' demand for different types of labor.

Our main empirical specification is a long-differences regression of changes in labor outcomes from 2010 to 2018 on changes in the firm-level share of AI workers during the same period, following the standard approach in settings with slow-moving processes like technological change (e.g., Acemoglu and Restrepo, 2020). As shown in Babina et al. (2021), AI investments accumulate gradually over time and generate effects that are not immediate, making the long-differences strategy well-suited for our setting. Furthermore, by taking first differences in independent and dependent variables, the long-differences specification ensures that time-invariant firm characteristics do not drive the results. To bolster causal interpretations of the results, we include a rich set of controls featuring industry fixed effects and firm-, industry-, and commuting-zone-level characteristics in 2010. All of our coefficient estimates are remarkably consistent across specifications with and without these detailed controls.

In terms of hierarchical structure, we provide evidence that AI is associated with firms becoming flatter, with higher shares of employees in entry-level or single-contributor roles and fewer employees in either middle-management or senior roles. Specifically, a one-standard-deviation change in the share of AI workers at a firm is associated with a 1.6% increase in the share of junior employees from 2010 to 2018, while middle management declines by 0.8% and senior management by 0.7%. This result is consistent with the channel suggested by Garicano and Rossi-Hansberg (2006) and explored by Bloom et al. (2014), where reductions in costs of accessing knowledge through improved data processing, such as AI technology, result in increased problem-solving ability of employees at all levels, leading to increased span of control and less reliance on top-heavy hierarchical structures.

In terms of labor composition, we observe a general upskilling trend associated with larger AI investments. Firms that invest more in AI tend to increase their shares of workers with bachelors, masters, and doctoral degrees (correspondingly decreasing the share of workers without college education). For example, a one-standard-deviation increase in the firm's share of AI workers translates into a 3.7% increase in the share of workers whose maximal educational attainment is an associates or bachelors degree, a 2.9% increase in the share of workers whose maximal educational attainment is a masters degree, and a 0.6% increase in doctoral degrees. These increases in educated workers correspond to a 7.2% decline in the share of workers without college education. The upskilling shifts in education are also observed in the firms' explicit labor demand in the Burning Glass job postings, which feature both required education and required number of years of prior experience for prospective job applicants. A one-standard-deviation increase in the share of AI workers is associated with a 0.5 additional year of required education in the firm's new job openings.

The additional demand for education in AI-investing firms tends to concentrate in technical fields. Leveraging the information on majors of the most recent degree for each individual employee in the resume data, we observe that AI investments are associated with a significant increase in the share of employees with majors in STEM degrees and a corresponding decline in the share of employees with degrees in social science and medicine fields. Similarly, the skill requirements in Burning Glass job postings reveal that AI-investing firms experience a significant increase in demand for employees with skills in data analysis and IT, while decreasing their search for employees with skills in traditional operational fields such as maintenance.

Our work contributes to the recent literature on the impact of AI technologies on the labor market. Previous literature has conjectured that AI has the potential to displace some human tasks, including high-skilled tasks (Acemoglu and Restrepo, 2019; Webb, 2020). Empirically, prior work made progress in measuring exposure to AI at the occupation level (Felten et al., 2018; Brynjolfsson et al., 2018; Webb, 2020) and the impact of AI on overall labor demand and employment at the firm level (Acemoglu et al., 2021; Babina et al., 2021).[1] Our paper is the first to document the relationship between the use of AI technologies and the composition and organization of the workforce at the firm level. While Babina et al. (2021) show that AI investments increase firm employment, our evidence further shows that the increase in employment is concentrated in highly-educated workers and high-skill workers with STEM backgrounds and IT skills. A potential explanation for our findings is that AI-fueled product innovation—the main channel through which AI investments seem to power firm growth so far, as shown in Babina et al. (2021)—increases firms' demand for complementary skilled labor.

Our paper is also related to the literature on previous general purpose technologies (such as IT) and labor composition and workplace organization. Prior literature documents that technologies like IT and electricity favor high-skilled labor but displace medium-skilled workers (Autor et al., 1998, 2003; Fizsbein et al., 2020). Bessen et al. (2022) find that IT investments are associated with an increase in the returns to skill at the firm level. We show that AI investments are associated with an increase in firms' hiring of skilled labor on aggregate, but these effects are heterogeneous. Demand for some high-skilled labor (e.g., STEM majors, IT skills) rises, while demand for other medium-skilled or high-skilled labor (e.g., finance, maintenance) declines. Our evidence on firms' hierarchical structures also contributes to the literature on technology and firm organization: firms investing in AI technologies become less top-heavy, which is similar to the previously-documented effect of IT but opposite to the effect of communication technologies (Acemoglu et al., 2007; Bloom et al., 2014). The combination of our results on organizational structure becoming flatter with AI investments and the demand for skilled human capital generally rising complements the work of Caroli and Van Reenen (2001). They document general complementarity between organizational change and demand for more skilled employees using establishment-level data in France and the U.K. Our results find analogous patterns with AI investmetns in U.S. firms and support the notion that new technologies such as AI can be an important driver of skill-biased organizational change.

The remainder of the paper is organized as follows. We introduce our data in Section 1 and detail our methodology for measuring AI investments and workforce composition in Section 2.

[1] Acemoglu et al. (2021) use firms' occupational structure to proxy for *exposure* to potential displacement by AI and explore how this exposure relates to firms' labor demand. By contrast, we study the effect of firms' AI *investments* on actual worker composition, including new hires and departures..

Section 3 explores how firms' initial workforce composition predicts AI investments, while Section 4 presents our main results on the relationship between AI investments and changes in workforce composition and organization. Section 5 concludes.

1 Data

To investigate how the composition and structure of firms' workforces changes in firms that invest more heavily in AI, we bring together two datasets. First, we take advantage of a unique matched employer-employee dataset built from resumes and featuring individual employees' detailed job descriptions and educational backgrounds. Second, we supplement the resume data with a comprehensive dataset of job postings revealing firms' demand for education and skills.

1.1 Employment profiles from Cognism

We leverage the employment profile (resume) dataset from Cognism, which offers matched employer-employee data covering approximately 535 million individuals globally. These data are introduced in detail in Fedyk and Hodson (2019) and Babina et al. (2021) and bring several key advantages that complement existing administrative data. First, Cognism offers broad coverage in the U.S., covering 64% of the full-time U.S. workforce as of 2018.[2] Second, while Cognism does not have information on wages (as would be included, for example, in the U.S. Census Bureau's Longitudinal Employer-Household Dynamics program), the Cognism data provide detailed information on individual workers' occupations, job tasks, and backgrounds—the kind of information that is not available in administrative data. Specifically, for each individual, we observe the start and end dates of each job, the job title (often along with a detailed job description), each job's company name and location, the individual's educational record (with university names, degrees, and majors), as well as any patents, awards, or publications that the individual chooses to include on the resume. This allows us to examine how firms' investments in new technologies such as AI interplay with granular changes in their workforce composition, including employee educational attainment, specialization, and seniority. Finally, the Cognism data also brings advantages relative to the job postings data that have been previously used to understand the impact of AI on the labor markets (e.g., Alekseeva et al., 2020; Acemoglu et al., 2020; Babina et al., 2021). Working

[2] Although our Cognism data snapshot is from July 2021, we follow Tambe et al. (2020) and Babina et al. (2021) and only use the years through 2018 to avoid potential noise from workers updating their resumes with a delay.

directly with employee resumes enables us to see who is actually working at each firm, rather than only firms' demand for employees, and captures changes in the workforce composition that occur outside of new hiring (e.g., promotions, onboarding of new employees through acquisitions, or layoffs of existing employees).

Cognism's AI Research department leverages techniques from machine learning and natural language processing, including named entity disambiguation and graph-based modeling methods, to further enrich the resume data by normalizing job titles and occupations, associating employees with functional divisions and teams within each firm, and identifying institutions, degrees, and majors from education records. We match employer names in the Cognism data to the names of publicly traded firms in the Compustat dataset using the approach developed in Fedyk and Hodson (2019). The matching of individual resumes to firm entities is performed dynamically to account for acquisitions and divestitures. We limit our attention to public firms with data in Compustat in order to include detailed controls for other firm characteristics (including sales, cash reserves, R&D expenditures, and markups) and to aggregate employee-level data to the firm level. The data include 657 million US-based person-firm-year observations between 2007 and 2018, of which 120 million (18%) are matched to U.S. public firms. This is consistent with prior statistics showing that publicly listed firms account for approximately 26% of overall U.S. employment (Davis et al., 2006). The sample of 120 million person-firm-years matched to U.S. public firms corresponds to 19 million distinct individual employees.

1.2 Job Postings from Burning Glass

The second dataset we use covers over 180 million job postings in the United States in 2007 and 2010–2018. The dataset is provided by Burning Glass Technologies (BG), which examines over 40,000 online job boards and company websites, collects the job postings data, parses them into a machine-readable form, and uses the data to construct labor market analytics products. BG employs a sophisticated deduplication algorithm to avoid double-counting vacancies that post on multiple job boards. BG data are quite comprehensive, covering approximately 60–70% of all vacancies posted in the U.S., either online or offline.[3] The data contain detailed information for each job posting, including the job title, location, occupation, and employer name. Most importantly for our paper, the job postings are tagged with (i) thousands of specific skills standardized from

[3] See Hershbein and Kahn (2018) for a detailed description of the BG data, including their representativeness, which is stable over time at the occupation level.

the open text in each job opening and (ii) specific requirements such as years of education and experience.

We focus on jobs with non-missing employer names (approximately 65% of all job postings) and at least one required skill (which corresponds to 93% of all job postings). Since we are interested in the composition of a firm's core workforce, we drop job postings that are internships. We match the employer firms in the remaining job postings to Compustat firms using fuzzy matching after stripping out common endings such as "Inc" and "L.P.". For observations that do not match exactly on firm name, we manually assess the top ten potential fuzzy matches based on the firm name, industry, and location. Out of 112 million job postings with non-missing employer names and skills, 42 million (38%) are matched to Compustat firms. This slightly over-represents employees of publicly listed firms, which constitute just over one fourth of U.S. employment in the non-farm business sector (Davis et al., 2006).

1.3 Additional Data Sources

We merge the Cognism resume data and the Burning Glass job postings data to several additional data sources. We collect commuting-zone-level wage and education data from the Census American Community Surveys (ACS) and industry-level wages and employment data from the Census Quarterly Workforce Indicators (QWI). Firm-level operational variables (e.g., sales, cash, assets) come from Compustat.

2 Methodology and Descriptive Statistics

2.1 AI Investments

We leverage the methodology proposed by Babina et al. (2021) to measure firms' investments in AI based on their intensity of AI-skilled hiring. The intuition is that successful implementation and use of AI technologies by firms requires employees with expertise in AI methods. In order to identify AI expertise, we take advantage of (i) the detailed information on required skills in the job postings data and (ii) new, data-driven methodology for identifying AI-related jobs. Previous methods for classifying job postings based on the presence of key terms from a pre-specified list (e.g., Hershbein and Kahn, 2018 ;Acemoglu et al., 2021;Alekseeva et al., 2020) are likely to suffer from both Type I (incorrectly labeling tangentially-related employees as AI-related) and Type II (missing real AI skills that did not make the initial dictionary) errors due to the arbitrariness of the list of keywords. This is especially relevant in a quickly-evolving domain such as AI, with new emerging skills that can be easily missed. The methodology from Babina et al. (2021) circumvents these challenges by learning the AI-relatedness of each of approximately 15,000 unique skills directly from the job postings data, based on their empirical co-occurrence (within required lists of skills across job postings) with unambiguous core AI skills. We then take skills that are empirically most related to the core AI skills and search for those in employment profiles in our resume data: we classify employees into AI-skilled workers and non-AI-skilled workers based on whether their job title, job description, and patents or publications produced during the job contain the highly-AI-relevant skills or core AI skills. Finally, we aggregate the worker-level data to the firm-level, annual panel data by calculating the share of the firm's employees who are AI-skilled.

More specifically, we start by measuring the AI-relatedness of each skill in the job postings data by calculating that skill's co-occurrence with Artificial Intelligence (AI) and its three main sub-fields: machine learning (ML), natural language processing (NLP), and computer vision (CV):

$$w_s^{AI} = \frac{\text{\# of jobs requiring skill } s \text{ and (ML, NLP, CV, or AI in required skills or in job title)}}{\text{\# of jobs requiring skill } s}$$

Intuitively, this measure captures how correlated each skill s is with the core AI skills. For example, the skill "Recurrent Neural Network" has a value of 0.965, which means that 96.5% of job postings that list "Recurrent Neural Network" as a required skill also require one of the core AI skills or contain one of the core AI skills in the job title. Thus, a "Recurrent Neural Network" requirement in a job posting is highly indicative of that job being AI-related. On the other hand, the AI-relatedness measure of the skill "Microsoft Office" is only 0.003. In Table 1 (reproduced from Babina et al., 2021) we list the skills with the highest AI-relatedness measures—namely, the skills that co-occur with the core AI skills in at least 70% of all job posting.

In the Cognism resume data, we identify AI-skilled employees as those whose job positions directly involve AI. We begin with the set of 67 keywords in Table 1, which have the highest skill-level AI-relatedness measures in the job postings data. We then consider every employment record of each individual in the resume data and identify whether any of these 67 AI-related terms appear in: (i) the job title or description; (ii) any patents obtained during the year of interest or the two following years (to account for the time lag between the work and the patent grant); (iii) any publications during the year of interest or the following year; or (iv) any awards received during the year of interest or the following year. If any of these conditions are met, then we classify that employee at that firm in that year as AI-related. For example, jobs with titles such as "senior **machine learning** developer" or publications such as "A new cluster-aware regularization of **neural networks**" are identified as AI jobs.

To aggregate to the firm level, we use the number of AI-related employees and the number of total employees at each firm in each year and compute the percentage of employees of that firm in that year who are classified as AI-related. Given that our empirical analyses focus on U.S.-listed firms, our firm-level measure focuses on the employees who are based in the U.S. Babina et al. (2021) provide a detailed discussion of this measure, perform multiple validation exercises, and offer detailed case studies of AI investments by individual firms in our sample. For the sake of brevity, we do not reproduce that analysis in this paper.

2.2 Labor Composition

We use the resume data to examine three aspects of firms' labor force: (i) educational attainment in terms of college and post-graduate degrees; (ii) specialization in terms of college majors (e.g., STEM vs. humanities vs. social science); and (iii) hierarchical structure in terms of the composition of employees across different levels of seniority. We describe the construction of each of these variables in turn below.

Educational attainment. Cognism uses the educational information from the resumes to classify each individual at each point in time based on that individual's highest educational attainment to date. The categories are: (i) no secondary education; (ii) associates degree; (iii) bachelors degree; (iv) masters degree other than an MBA; (v) MBA; and (vi) doctoral degree (including Ph.D. and J.D. degrees). For each firm in our sample, we compute four educational attainment variables: (i) the share of employees in each year who have a college degree (either a bachelors or an associates), (ii) the share of employees who have at least a masters degree, (iii) the share of employees who have a doctoral degree, and (iv) the share of employees who do not have a college degree. Figure 1 plots the mean of these four shares in the resume data for the sample of Compustat firms. The Cognism data slightly oversamples educated workers, with over 60% of employees holding at least some post-secondary degree.

Educational specialization. Cognism extracts major information from individual's education records and groups majors into broad categories of (i) Humanities, (ii) Social Sciences, (iii) Science, Technology, Engineering, and Mathematics (STEM), (iv) Fine Arts, (v) Medicine, and (vi) Other. We take these broad classifications and compute, for each firm in each year, the share of current employees whose most recent degrees fall in each category. Figure 2 plots the distribution of majors based on the most recent degree in the resume data for the sample of Compustat firms.

Seniority. The Cognism data are enriched with state-of-the-art machine learning techniques to identify employees' departments and seniority. First, over 20,000 individual job titles are classified manually based on markers of seniority and department. The remaining job titles are then classified into departments using a probabilistic language model and into seniority levels using an artificial neural network. There are six levels of seniority in total: (i) entry-level positions where individuals start straight out of undergraduate or high school education, (ii) experienced staff in roles such as individual senior contributor but not managing others, (iii) team leads who manage others but have little to no company-level decision-making responsibility, (iv) middle management roles that oversee several smaller teams, (v) leadership positions that head larger departments or business segments, and (vi) executive-level leadership such as the Chief Executive Officer and Chief Operating Officer. Fedyk et al. (2021) perform an evaluation of Cognism's seniority classification on the sample of accounting firms by assessing the model's output against a manually reviewed sample of over 10,000 positions. They find that Cognism's seniority classification has an accuracy rate of over 95%. In this paper, we group the seniority levels into three broader bands: low (consisting of entry-level positions and experienced individual contributors), medium (team leads and middle management), and high (leadership and the executive level). Figure 3 plots the shares of workers in each of these three seniority levels based on the resume data for the sample of Compustat firms. Overall, nearly 70% of employees are in junior-level or non-supervisory roles, with 20% in mid-tier and 11% in senior management.

2.3 Labor Demand

We use the job postings data from Burning Glass to measure two aspects of firms' labor demand: required education and experience; and required skills. Since these measures are calculated from firms' job postings, they only measure firms' labor demand—the types of workers firms wish to hire—instead of the types of workers working at the firm.

Required education and experience. For each job posting, Burning Glass codes the minimum years of required education and the minimum years of required experience. 59% of job postings specify an education requirement, which averages 14.5 years of school. 52% of job postings specify a requirement for prior work experience in related fields, which averages 4 years. Figure 4 plots the distribution of the number of years of minimum education required and the number of years of minimum experience required (using job postings that specify a given requirement). Hershbein and Kahn (2018) show that average education requirements in Burning Glass align well with the education levels of employed workers at the occupation and MSA levels.

Skill clusters. Burning Glass groups all skills into one of 28 skill clusters. Skill clusters are groupings of skills that have similar functionality, can be trained together, and/or frequently appear together in job postings. For example, the skill "Python" belongs to the "Information Technology" skill cluster, and the skill "Machine Learning" belongs to the "Analysis" skill cluster. Table 2 presents the top five skills (i.e., skills appearing in the largest number of job postings) for each skill cluster.

For each job posting, we calculate the share of required skills that fall within each skill cluster. For example, if a job posting requires "Python" and "Machine Learning," then the share of the "Information Technology" skill cluster and the share of the "Analysis" skill cluster are both 50%. We then average these shares across all job postings of a given firm in a given year. Thisresults in a weighted share of job postings that require skills in each skill cluster.[4] The shares of all 28 skill clusters add up to one.

2.4 Descriptive Statistics

We present summary statistics for each of our measures of worker composition. We start by documenting the variation of education levels of workers over time and across geographic areas. Figure 5 plots the share of workers in four education levels (undergraduate, masters, doctoral, and less than college) based on the Cognism resume data over time. The share of workers in each education level is mostly flat over time, with an intuitive slight upward trend in the share of workers with undergraduate degrees and slight downward trend in the share of workers with no post-secondary education. This suggests that the representativeness of the Cognism resume data across education categories is stable over time. Specifically, while Cognism does offer more comprehensive coverage of more educated workers, this does not change over time, and there is no differential over-representation of highly-educated workers in some periods versus others. Figure 6 considers the job postings data and shows the average required number of years of education in each state. Intuitively, states such as Massachusetts, California, and Illinois have the highest demand for highly-educated workers.

[4]This is equivalent to weighting each skill required by a job posting by the inverse of the total number of skills required by the job posting. We do not directly compute the share of job postings requiring skills in a skill cluster, because generic skills like "communication" are required by most job postings, although they constitute a small part of the job requirements for each job posting.

Next, we look at the distribution of workers' education levels and specialization across industries. Figure 7 plots the average share of workers with undergraduate, masters, and doctoral degrees in the Cognism resume data for public firms in each of the 2-digit NAICS sectors. Firms in the "Education Services" sector and the "Professional and Business Services" sector have the highest shares of workers with undergraduate degrees, masters degrees, and doctoral degrees. Figure 8 considers the distribution of workers' educational majors across industries. We see intuitive trends that help validate Cognism's classification of educational majors: the tech sectors ("Professional and Business Services" and "Information") have the highest shares of workers with STEM majors, "Finance/Insurance" and "Real Estate" have the highest shares of workers with social science majors (which include all business school degrees such as MBAs), and the "Health Care" sector has the highest share of workers with degrees in medicine fields.

Finally, Figure 9 considers the distribution of workers' seniority levels across industries. We observe that all industries have a pyramid structure, with the majority of workers in low seniority levels and a small percentage of workers in high seniority levels. The only exceptions are "Arts/Entertainment" and "Health Care," which are top-heavy with more workers in senior positions than in mid-level positions. Given the relative homogeneity of hierarchical structures across diverse industry sectors, even small changes in the proportion of employees in different levels would be a meaningful indicator of shifts in a firm's organizational structure.

3 Does Ex-ante Labor Composition Predict Growth in AI Investments?

We consider the determinants of firms' investments in AI technologies and whether firms' initial labor composition can predict future AI investments. Theoretically, firms' initial labor composition could affect both their demand for AI investments and their ability to invest in AI by attracting AI talent. For example, Bresnahan (2019) and Agrawal et al. (2021) argue that, theoretically, the degree of modularity in the organizational structure of a firm could impact the firm's ease of AI adoption. When modularity is high, tasks are more independent, and there is less need for coordination; as a result, it is easier to implement AI and change decision making in one part of the organization, as it does not require changes elsewhere. In terms of employee specialization, Acemoglu et al. (2020) show that establishments with occupations that are more exposed to AI technologies have a higher demand for AI workers. And in terms of firms' workforce education, Babina et al. (2021) document that firms with alumni connections to universities that are historically strong in AI research invest more in AI by being able to attract AI-trained students from those universities.

We are interested in understanding the *use* of AI technologies by a wide range of firms. In order to not conflate this with the invention of new AI tools, we exclude firms in the tech sector (2-digit NAICS 51 or 54) from our empirical analyses. In Table 4, we examine how ex ante worker composition predicts future growth in firm-level AI investments by estimating the following long-differences specification:

$$\Delta ShareAIWorkers_{i,[2010,2018]} = \beta WorkerComposition_{i,2010} + IndustryFE + \epsilon_i, \quad (1)$$

where $\Delta ShareAIWorkers_{i,[2010,2018]}$ denotes the change in the share of firm i's AI-skilled employees from 2010 to 2018, standardized to mean zero and standard deviation one to streamline the economic interpretation. All regressions include 2-digit NAICS industry fixed effects. The explanatory variables include the following measures of ex-ante worker composition measured as of 2010: the shares of workers in each seniority level in column 1, the shares of workers in each education level in column 2, and the shares of workers in each major in column 3. We leave out one of the shares in each column due to collinearity arising from the shares of all groups summing to one (we omit the share of workers in the high seniority level in column 1, the share of workers with no college degree in column 2, and the share of workers with other majors in column 3). Column 4 includes all variables in a multivariate specification. All continuous variables are winsorized at 1% and 99% to limit the influence of outliers. We weigh the estimating equation by each firm's total number of employees in the Cognism resume data in 2010 to account for potential differences in precision in the measurement of AI investments across firms with different coverage.

The results in Table 4 highlight that firms with more workers with doctoral degrees and more workers with STEM majors invest more in AI going forward. This is broadly consistent with the evidence in Babina et al. (2021) that firms with more workers in fields related to AI and more educated workers are able to attract AI talent more easily. The hierarchical structure of the firm does not significantly predict AI investments.

4 AI Investments and Labor Composition

We explore how the key aspects of firms' labor composition change with firms' investments in AI. Firms that invest more in AI shift towards more educated workforces, with more emphasis on STEM degrees and skills in analysis and IT. At the same time, AI-investing firms become less top-heavy in terms of their hierarchies, with increasing shares of junior employees and less emphasis on middle-management and senior roles.

4.1 AI Investments and Employee Seniority

We begin the analysis by examining whether firms that invest in AI become more top-heavy or bottom-heavy in terms of their hierarchical structure. The direction of this shift is ex ante ambiguous and an open empirical question. On the one hand, AI contributes to firm growth (Babina et al., 2021), and as enterprises have grown in size over the 20th century, the share of employees in managerial positions has risen dramatically (Radner, 1992). Thus, AI-fueled growth may result in the continuation of this trend towards increased organizational complexity and increased need for middle- and top-level managerial positions. For example, Caliendo et al. (2015) show that many firms expand by adding layers of management. On the other hand, Garicano and Rossi-Hansberg (2006) present a theoretical model where reductions in costs of accessing knowledge through improved data processing (which is arguably the main effect of AI technology) result in increases in the problem-solving ability of employees at all levels, leading to increased span of control and less reliance on top-heavy hierarchical levels.

Previous technologies also had differing impacts on firm organization. Acemoglu et al. (2007) show that firms investing in new information technologies are more likely to favor decentralization. Bloom et al. (2014) find that information technology and communication technology have opposing effects on firm organization: information technology is a decentralizing force allowing workers and lower-level managers to handle more problems, while communication technology decreases autonomy and is associated with more centralization.

Empirically, we measure hierarchical flatness as the share of a firm's overall employees who are in more junior versus more senior positions: if firms become more top-heavy, increasing their middle-management and senior roles, then the share of employees in senior positions will rise, and vice versa. We link the changes in the shares of employees across levels to firms' AI investments using long-differences regressions, which are standard in settings analyzing slow-moving processes like technological progress (Acemoglu and Restrepo, 2020) and especially well-suited to study AI investments, which are gradual over time and have effects that are not immediate (Babina et al., 2021). Specifically, we regress firm-level changes in the share of junior, middle-ranked, and senior employees from 2010 to 2018 on changes in AI investments proxied by the growth in the share of AI workers. By taking first differences in independent and dependent variables, the long-differences specification ensures that time-invariant firm characteristics do not drive the results. In Table 5, we report the estimates from the following regression:

$$\Delta SeniorityLevel_{i,[2010,2018]} = \beta \Delta ShareAIWorkers_{i,[2010,2018]} + Controls'_{i,2010}\gamma + IndustryFE + \epsilon_i, \quad (2)$$

where the main independent variable, $\Delta ShareAIWorkers_{i,[2010,2018]}$, captures the change in the share of AI workers in firm i from 2010 to 2018, standardized to mean zero and standard deviation of one as in Table 4. $IndustryFE$ are 2-digit NAICS fixed effects. As in Section 2.4, we focus on firms in non-tech sectors. In columns 1, 3, and 5 we include only industry fixed effects to examine the unconditional relationship between changes in AI investments and employee seniority. In columns 2, 4, and 6, we add a rich set of controls proposed by Babina et al. (2021) and measured at the start of the sample period in 2010: (i) firm-level characteristics (log sales, cash/assets, R&D/Sales, log markup, and the log of the firm's total number of jobs); (ii) characteristics of the commuting zones (CZ) where each firm is located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers); and (iii) the log industry-average wage. Summary statistics on key variables for the regression sample are provided in Table 3.

In columns 1 and 2 of Table 5, the dependent variable is the firm-level change in the share of junior employees (i.e., employees in entry-level and single-contributor positions) from 2010 to 2018. In columns 3 and 4, the dependent variable is the firm-level change in mid-level employees (i.e., team leads and middle managers), and columns 5 and 6 consider the firm-level change in senior employees (department heads and top-level leadership). The results reveal that AI-investing firms become flatter (or, more precisely, more bottom-heavy and less top-heavy). A one-standard-deviation increase in AI investments is associated with a 1.6% increase in the share of junior employees, accompanied by a 0.8% decline in both mid-level employees and senior management. Importantly, the results are identical with and without the inclusion of detailed ex-ante firm-level, location-level, and industry-level controls in even columns, despite the adjusted *R-Squared* rising significantly (nearly doubling for both the share of junior employees and the share of senior employees). This makes it unlikely that the results are driven by ex-ante omitted firm characteristics (Altonji et al., 2005; Oster, 2019).

The magnitude of the results in Table 5 is economically meaningful, given that the cross-sectional average change in the share of junior employees over the sample period is only 0.18%, and there has been no overall trends towards more junior employees across the cross-section of U.S. public firms. AI-investing firms experience fast shifts towards more junior employees and the reductions of senior-lever employees, consistent with the theoretical prediction of Garicano and Rossi-Hansberg (2006) and empirical evidence in Bloom et al. (2014) that technologies that improve prediction and decision-making, such as AI, will give lower-level workers more autonomy and require fewer managerial layers in firms.

4.2 AI Investments and Employee Educational Attainment

We leverage the detailed individual-level information in the resumes to study the association between the growth in firm-level AI investment and changes in the upskilling of the firms' workforces in terms of the employees' educational attainment. Educational attainment is a particularly relevant trend to investigate in the context of firms' AI investments, given the extensive labor economics literature on skill-biased technological change (Autor et al., 1998; Acemoglu and Autor, 2011; Autor et al., 2003; Katz and Murphy, 1992). Previous technologies such as IT have increased the relative demand for college graduates. In the case of AI, Babina et al. (2021) show that AI-investing firms engage in more product innovation, which may further increase firms' demand for skilled labor (Bresnahan et al., 2002). On the other hand, Webb (2020) predicts that AI is more likely to replace high-skilled tasks performed by highly-educated workers than previous technologies such as software and robots. Grennan and Michaely (2020) study the impact of AI on a particular group of high-skilled workers—security analysts,—and find that AI replaces some tasks but increases the importance of soft skills. Furthermore, changes to organizational hierarchies may induce shifts in labor composition, as flatter hierarchical structures could require higher human capital from each individual employee (Caroli and Van Reenen, 2001).

We investigate the extent to which AI, as a technology, is associated with labor shifts towards more educated workers by estimating the regression in Equation 2 and using the same independent variable and controls as in Table 5 but looking at the changes in levels of education attainment as the outcome variable. In Table 6, the dependent variable is the changes in the share of employees whose maximal attainment is a college degree in columns 1 and 2, the share of employees whose maximal attainment is a masters degree in columns 3 and 4, the share of employees with doctoral degrees in columns 5 and 6, and the share of employees with no college degree in columns 7 and 8.

The results confirm the prediction that larger AI investments are associated with educational upskilling of the workforce. Using estimates from even columns when all controls are included, a one-standard-deviation increase in AI investments is associated with a 3.7% increase in the share of college-educated workers, a 2.9% increase in employees with masters degrees, and a 0.6% increase in employees with doctoral degrees. Correspondingly, the share of employees with no college education declines by a substantial 7.3%. As with the results on seniority, the results on educational attainment are nearly identical with (even columns) and without (odd columns) the inclusion of detailed firm-level, location-level, and industry-level controls, indicating that these findings are likely not driven by omitted ex-ante variables. The results are also interesting in the light of relatively slow shifts in the educational makeup of the workforce in general shown earlier in Figure 5. The share of workers with advanced degrees (masters and doctoral) has remained practically flat from 2010 to 2018 in the overall workforce, as can be seen in Figure 5. By contrast, the share of employees with advanced degrees (both masters and doctoral degrees) has risen significantly in firms that have been investing in AI, suggesting that there is a reallocation of highly educated workers away from non-AI investing firms and towards firms that invest more heavily in AI.

The reason for the shift towards more educated workforces in AI-investing firms appears to be, at least in part, increasing demand for educated and experienced employees on the firms' side. In Table 7, we complement the results from the Cognism resume data with an analysis of labor-related outcomes measured using Burning Glass job postings. We estimate Equation 2 using the same independent variable and controls as in Tables 5 and 6, but with the dependent variables being: (i) the change in the average number of years of education required in the firm's job postings from 2010 to 2018 (columns 1 and 2), and (ii) the change in the average number of years of experience required in the firm's job postings from 2010 to 2018 (columns 3 and 4).[5] We observe that firms that invest more in AI look for more educated and more experienced workforces. For

[5]The sample size is smaller than in Table 6 because not all firms in the Cognism resume data are matched to job postings in Burning Glass data.

example, a one-standard-deviation increase in the share of AI workers from 2010 to 2018 is associated with additional 0.52 years of educational experience (column 2), reinforcing the increased educational attainment of actual workers that we observe in Table 6.

4.3 AI Investments and Employee Specialization and Skills

We consider one additional aspect of the changing workforce and its relationship to AI: the importance of technical and non-technical skills. A number of recent studies point out that it is specifically technical abilities that are uniquely important to modern firms. For example, document that engineers and scientists are among the employees whose net flows (net arrivals and departures) are most predictive of the firm's stock returns. Fedyk and Hodson (2019) show that technologies such as IT in the early 2000s and data analysis in 2010s can even be overvalued by corporate investors.

We use the resume data to observe whether AI investments are associated with broader changes in the technical specialization of AI-investing firms. Specifically, in Table 8, we re-estimate Equation 2 using the same independent variable and controls as in Tables 5 and 6, but the dependent variables being: (i) the share of employees whose most recent degree was in a STEM field in columns 1 and 2, (ii) the share of employees whose last degree was in social science in columns 3 and 4, (iii) the share of employees whose most recent degree was in fine arts in columns 5 and 6, (iv) the share of employees whose last degree was in humanities in columns 7 and 8, and (iv) the share of employees whose last degree was in medicine in columns 9 and 10.

The results reveal that increased AI investments are indeed associated with a general trend towards technically-skilled employees at the firm level. Using estimates from even columns when all controls are included, a one-standard-deviation increase in the share of AI workers at the firm is associated with a 2.9% increase in the share of employees whose most recent degree is in STEM. This increase is offset by declines in the shares of employees with social science, fine arts and medicine backgrounds.

Once again, we supplement our resume-based results with firms' demand from Burning Glass to see whether firms that invest more in AI start requiring more technical skills more generally. AI has been highlighted as a technology that can shift the skill requirements of the workforce by (Acemoglu et al., 2020), who also consider job postings and find that establishments with more occupations that are highly exposed to AI are associated with both increased redundancies in existing skills and more requirements of new skills. We focus on skill clusters, and for each skill cluster in Burning Glass, we estimate Equation 2 with the same independent variable and controls as in Tables 5–8 but the share of job postings within each specific skill cluster as the dependent variable. The results, reported in Table 9, show that the main skill shifts associated with firms' AI investments are (i) increased demand for data analysis skills (almost mechanically, given this is where many of AI-skilled jobs are), (ii) increased demand for IT skills (where some of AI-skilled job postings are) , and (iii) lower demand for maintenance skills. For example, a one-standard-deviation increase in the share of AI workers at a given firm from 2010 to 2018 corresponds to that firm increasing the share of its job postings requiring IT skills by 1.2%. These results suggest that AI skills, most of which belong to the data analysis skill cluster, are complementary to IT skills and can substitute for maintenance skills. Interestingly, firms that invest more heavily in AI do not reduce their demand for some of the skill groups that are most often predicted to be replaced by AI, such as customer service, HR, and legal skills.

5 Conclusion

In this paper, we study the relationship between the use of AI technologies and workforce composition and organization at the firm level. We find that firms that initially have a more educated workforce and higher emphasis on STEM workers are more likely to invest in AI. At the same time, firm-level growth in AI investments is associated with an increasingly flatter hierarchical structure, an increase in the share of workers with college degrees and advanced degrees, and a further increase in the share of workers with STEM majors. Data on job postings reveal that firms investing in AI technologies increase their demand for workers with more years of education and data analysis and IT skills

Our evidence of major changes in firms' workforce composition and organization accompanying AI investments contributes to our understanding of how AI can transform firms' organization and production processes. As a predictive technology, AI improves individual employees' ability to make predictions and decisions, which increases the autonomy of workers and reduces the demand for managerial positions. However, unlike previous automation technologies that displaced routine tasks, AI does not seem to reduce the demand for high-skilled workers performing prediction tasks, instead increasing the share of high-skilled labor at the firm level. Further understanding the interactions between AI technology, production processes, and firm organization would be a fruitful area for future work.

Our evidence also helps to shed light on the impact of AI on the labor market. At the firm level, AI only increases the demand for skilled labor and does not seem to displace tasks that are commonly predicted to be replaced by AI, such as customer service, human resources, and legal jobs. However, it remains an open question how these effects aggregate to the labor market level, and it is possible that AI displaces jobs in non-AI-investing firms. Furthermore, our results imply that there is a reallocation of skilled labor from non-AI-investing firms to AI-investing firms, which might have important implications for sorting and between-firm inequality in the labor market.

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Figure 1. Distribution of Education Levels in the Cognism Resume Data

This figure shows the fraction of workers in each education level (no college, college, master, and doctoral) in the Cognism data. The four education levels are mutually exclusive and each worker is counted once for their highest level of education. The sample includes all workers in Compustat firms between 2010 and 2018.

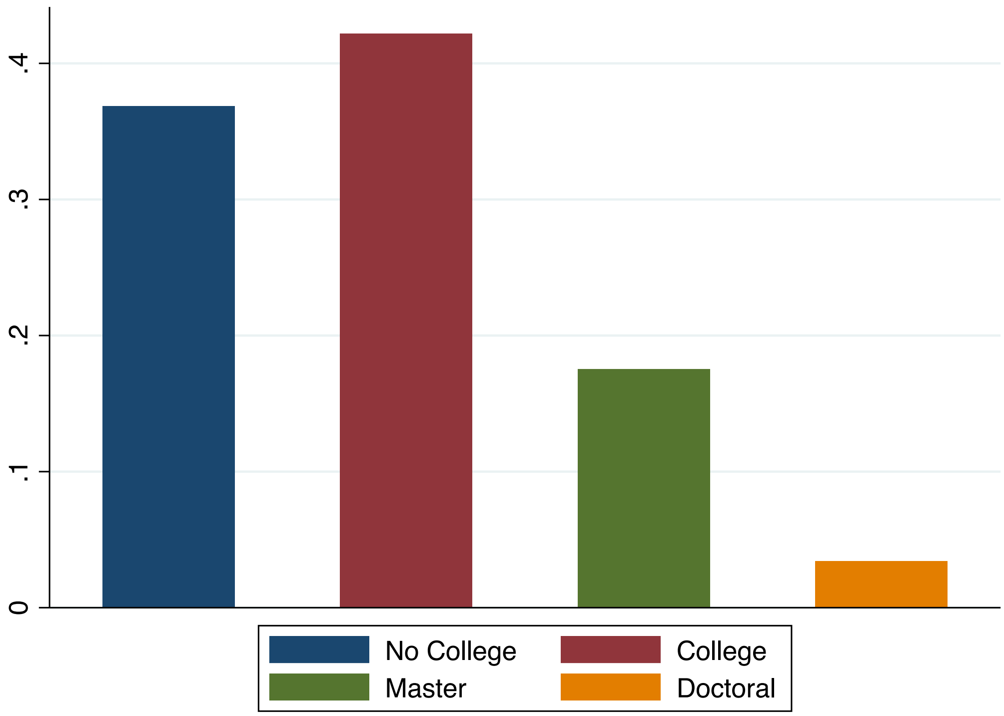


Figure 2. Distribution of Majors in the Cognism Resume Data

This figure shows the fraction of workers in each major (STEM, social science, fine arts, humanities, medicine, and other) in the Cognism data. STEM includes engineering (e.g., electrical, chemical, mechanical), physical sciences (e.g., math, physics, chemistry, computer science, statistics), and biological sciences (e.g., biology, pharmacology). The majors are mutually exclusive; for each worker, we record the major of the most recent degree earned. The sample includes all workers in Compustat firms between 2010 and 2018.

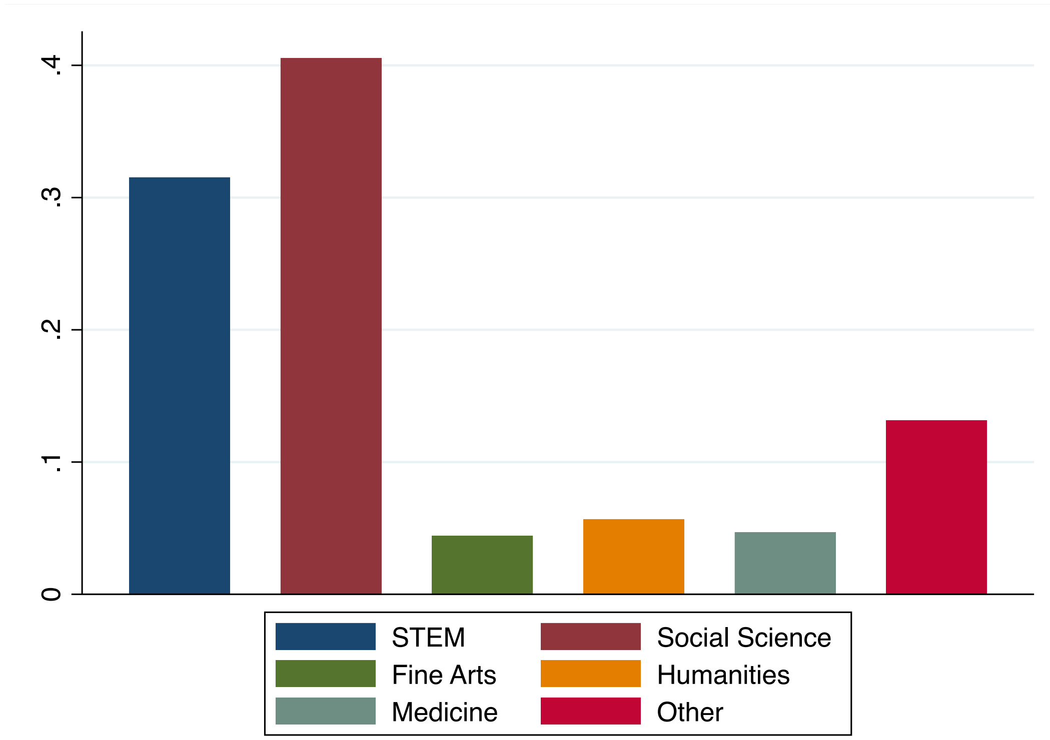


Figure 3. Distribution of Seniority Levels in the Cognism Resume Data

This figure shows the fraction of workers in each seniority level (low, medium, and high) in the Cognism data. The seniority levels are described in text. The sample includes all workers in Compustat firms between 2010 and 2018.

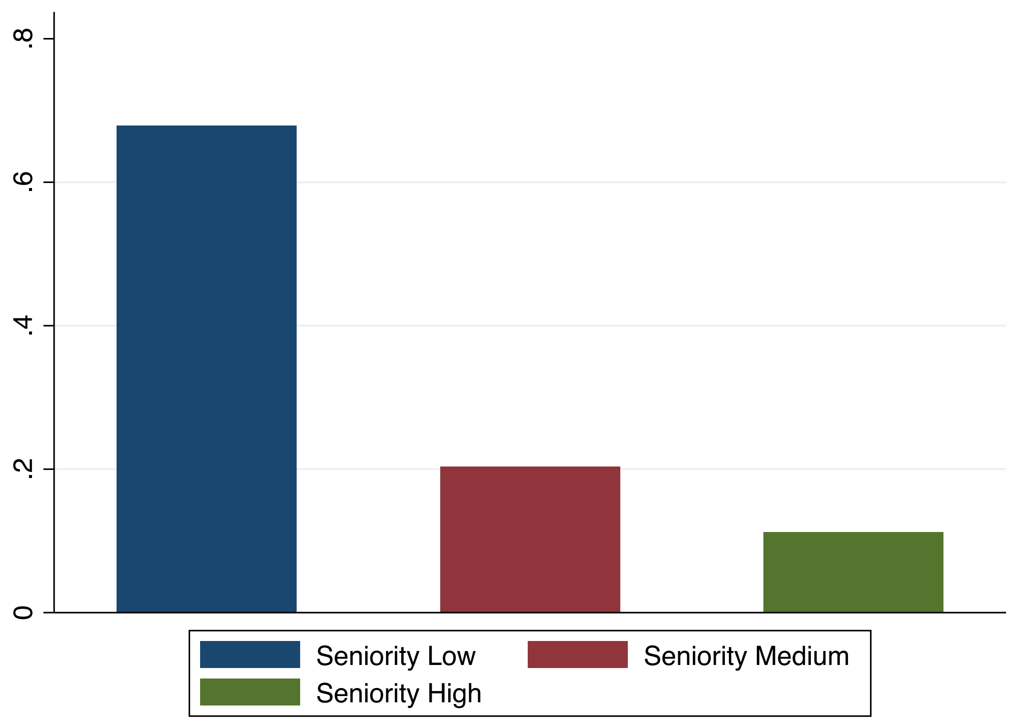
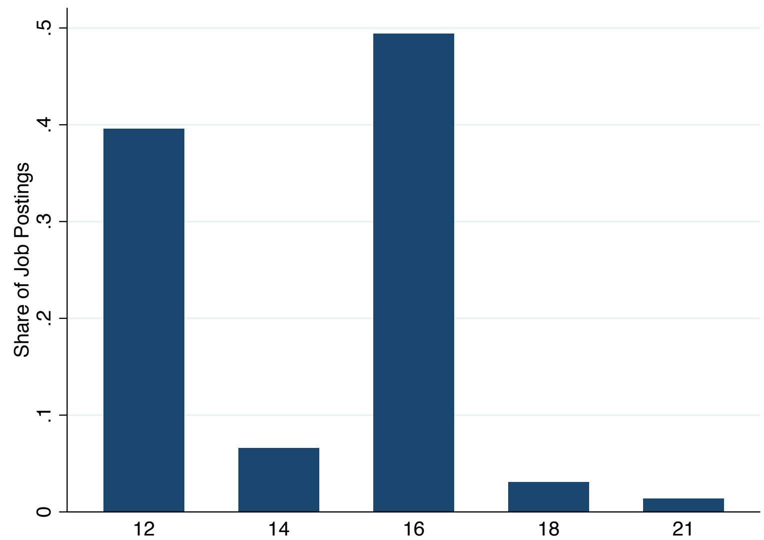
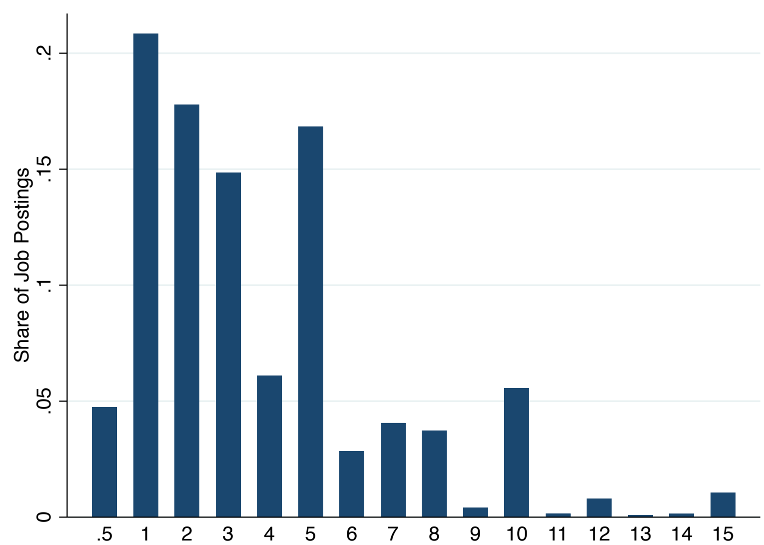


Figure 4. Distribution of Required Years of Education and Experience in the Burning Glass Job Postings Data

This figure shows the fraction of job postings with the number of years of required education (Panel (a)) or number of years of required work experience (Panel (b)) in the Burning Glass job postings data. The sample includes all job postings of Compustat firms between 2010 and 2018.



(a) Number of years of education



(b) Number of years of experience

Figure 5. Times Series of Workers' Education Levels in the Cognism Resume Data

This figure shows the time series of workers' education levels. Each line is the fraction of all employees (across all public firms) with each highest education level (less than college, college, master, or doctoral) in the Cognism resume data in a given year from 2010 to 2018.

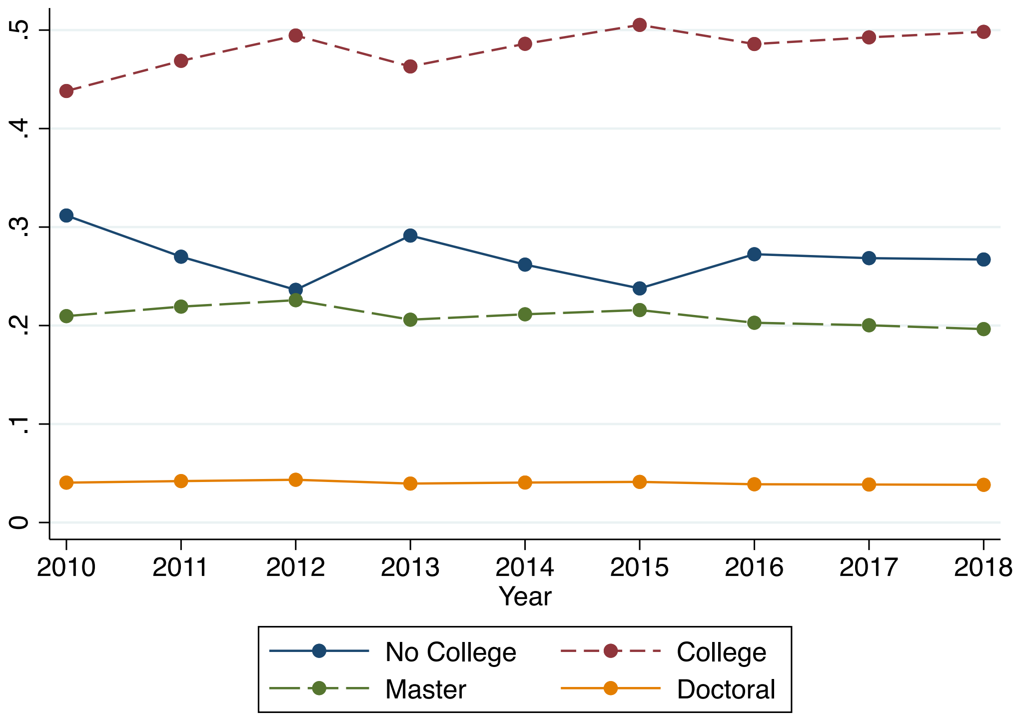


Figure 6. Map of Average Required Years of Education in the Burning Glass Job Postings Data

This figure shows a heat map of the average required years of education across U.S. states. It plots the average required years of education of job postings of public firms in each commuting zone from 2010 to 2018.

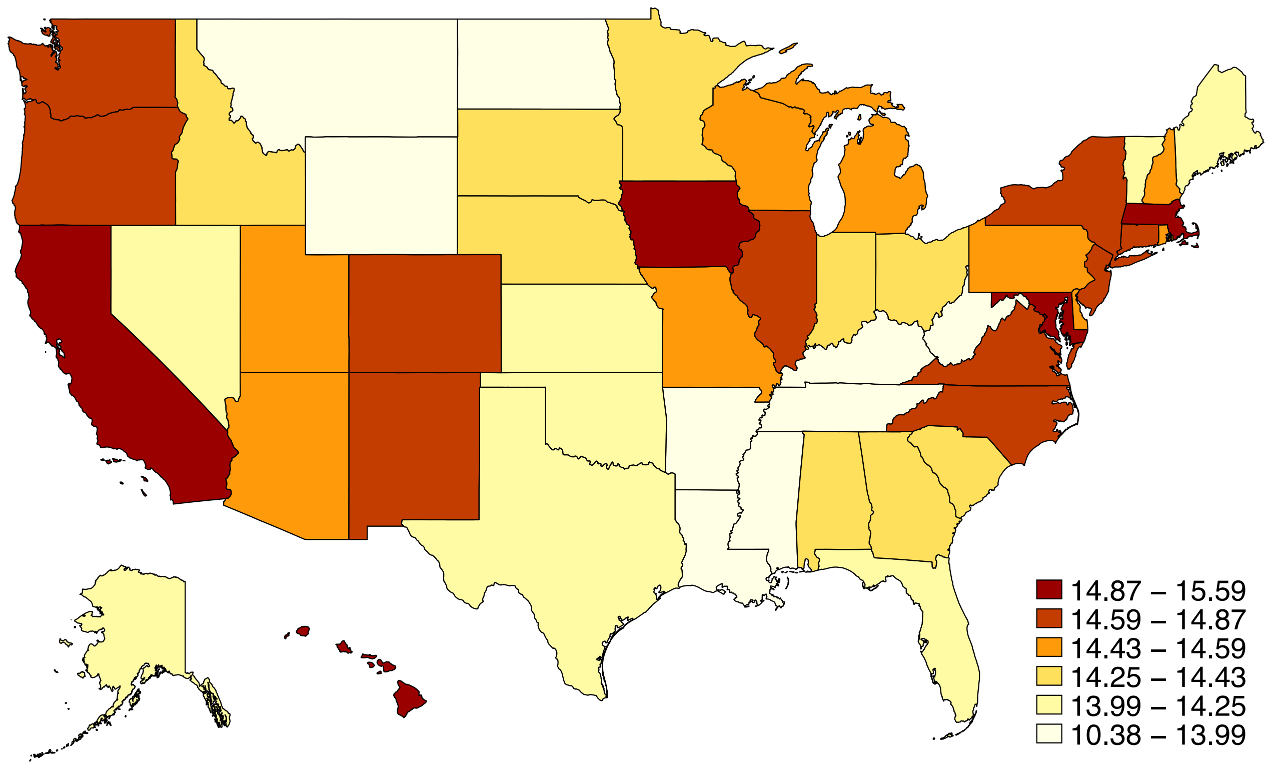


Figure 7. Education Level By Industry Sector in the Cognism Resume Data

This figure presents the share of workers in each highest level of education at the industry level, based on the sample of public firms. For each sector (based on NAICS-2 digit industry codes), we compute the share of workers with the highest level of education being less than college, college, master, or doctoral in the Cognism resume data.

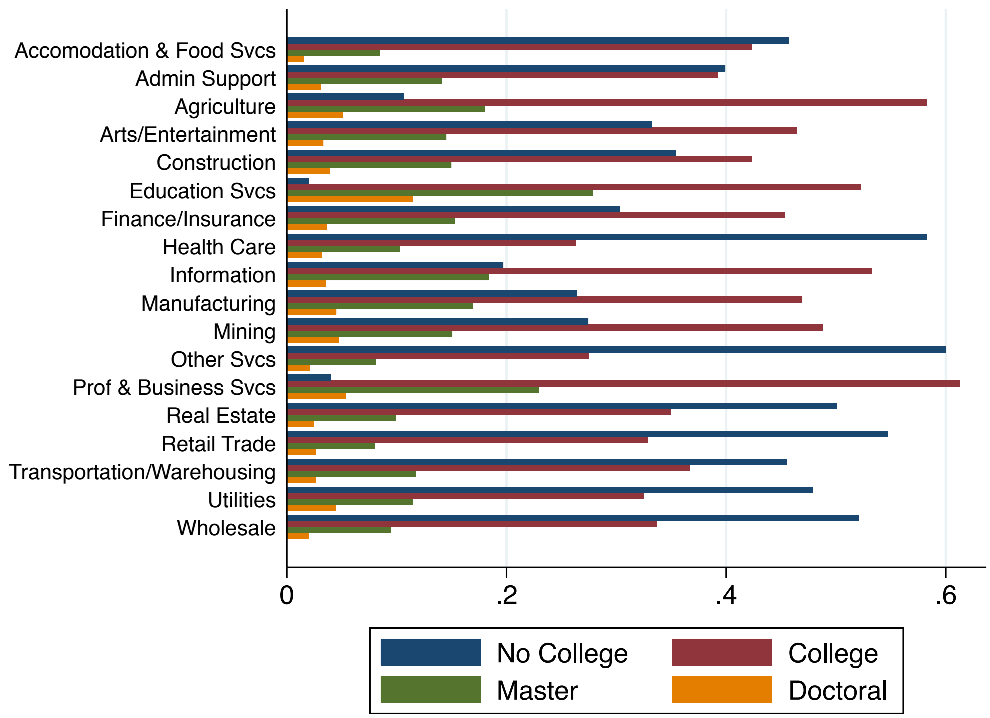


Figure 8. Distribution of Majors By Industry Sector in the Cognism Resume Data

This figure presents the share of workers in each seniority level in each major, based on the sample of public firms. For each sector (based on NAICS-2 digit industry codes), we compute the share of workers in each major (STEM, social science, fine arts, humanities, medicine, and other) in the Cognism resume data. STEM includes engineering (e.g., electrical, chemical, mechanical), physical sciences (e.g., math, physics, chemistry, computer science, statistics), and biological sciences (e.g., biology, pharmacology). The majors are mutually exclusive; for each worker, we record the major of the most recent degree earned.

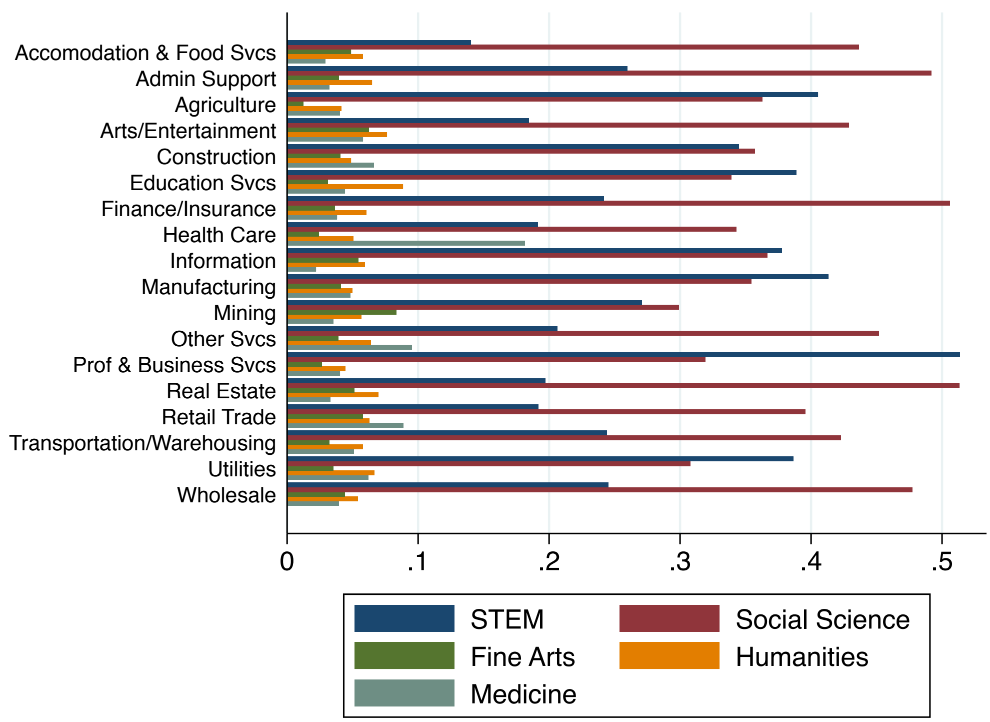


Figure 9. Seniority Level By Industry Sector in the Cognism Resume Data

This figure presents the share of workers in each seniority level at the industry level, based on the sample of public firms. For each sector (based on NAICS-2 digit industry codes), we compute the share of workers in each seniority level (low, medium, or high) in the Cognism resume data.

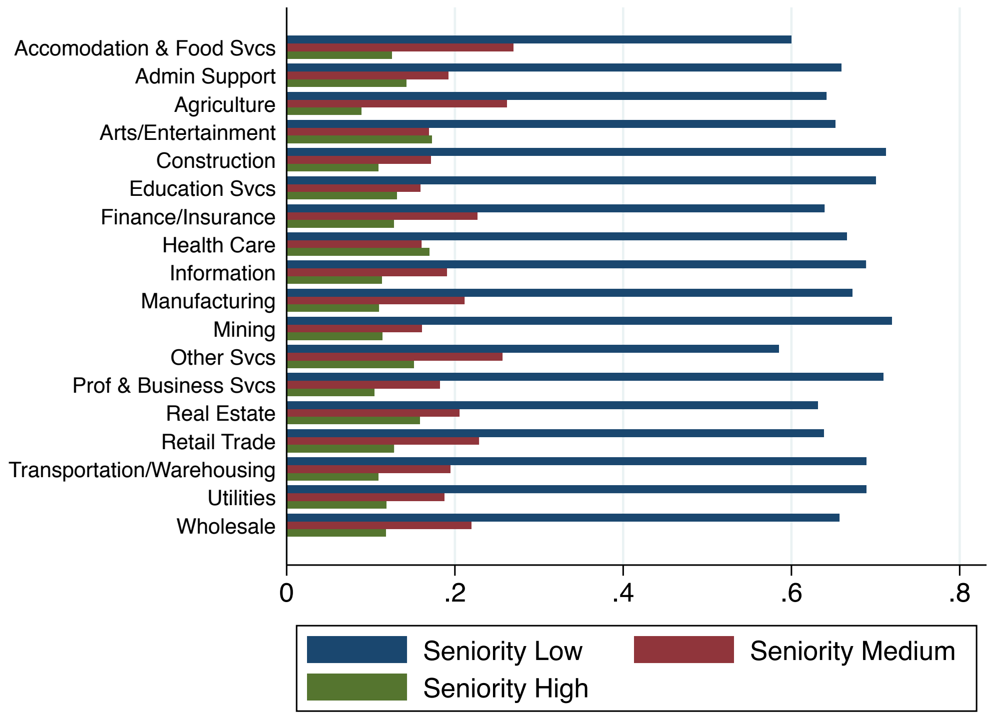


Table 1. Skills with Highest AI-Relatedness Measures in Burning Glass Job Postings

This table lists the top skills in the Burning Glass data ranked by the skill-level AI measure. For each skill, we report the percentage of jobs requiring that skill that also require one of the four core AI skills—artificial intelligence, machine learning, computer vision, and natural language processing. For example, for jobs that require "Recurrent Neural Network (RNN)," 96.5% also require one of the four core AI-skills. Only skills that appear in least 50 job postings are included.

#	Skills	AI-relatedness Score
1	Artificial Intelligence	1.000
2	Computer Vision	1.000
3	Machine Learning	1.000
4	Natural Language Processing	1.000
5	ND4J (software)	0.980
6	Kernel Methods	0.979
7	Microsoft Cognitive Toolkit	0.975
8	Xgboost	0.972
9	Sentiment Classification	0.971
10	Long Short-Term Memory (LSTM)	0.971
11	Libsvm	0.968
12	Semi-Supervised Learning	0.968
13	Recurrent Neural Network (RNN)	0.965
14	Word2Vec	0.956
15	MXNet	0.953
16	Caffe Deep Learning Framework	0.950
17	Autoencoders	0.949
18	MLPACK (C++ library)	0.942
19	Keras	0.941
20	Theano	0.938
21	Torch (Machine Learning)	0.932
22	Wabbit	0.929
23	Boosting (Machine Learning)	0.905
24	TensorFlow	0.904
25	Vowpal	0.903
26	Convolutional Neural Network (CNN)	0.897
27	Jung Framework	0.894
28	OpenNLP	0.894
29	Natural Language Toolkit (NLTK)	0.892
30	Unsupervised Learning	0.891
31	Dlib	0.891
32	Scikit-learn	0.889
33	Latent Semantic Analysis	0.889
34	Latent Dirichlet Allocation	0.889
35	Stochastic Gradient Descent (SGD)	0.881
36	Gradient boosting	0.872
37	Dimensionality Reduction	0.861
38	Deep Learning	0.859
39	DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	0.855
40	AI ChatBot	0.844
41	Recommender Systems	0.842
42	Random Forests	0.840
43	Deeplearning4j	0.839
44	Support Vector Machines (SVM)	0.817
45	Unstructured Information Management Architecture	0.806
46	Apache UIMA	0.805
47	Maximum Entropy Classifier	0.799
48	Hidden Markov Model (HMM)	0.796
49	Pybrain	0.786
50	Computational Linguistics	0.780
51	Naive Bayes	0.768
52	H2O (software)	0.763
53	Expectation-Maximization (EM) Algorithm	0.763
54	WEKA	0.761
55	Clustering Algorithms	0.740
56	Matrix Factorization	0.739
57	Object Recognition	0.727
58	Classification Algorithms	0.721
59	Information Extraction	0.709
60	Image Recognition	0.706
61	Bayesian Networks	0.705
62	Supervised Learning (Machine Learning)	0.695
63	OpenCV	0.688
64	K-Means	0.683
65	Sentiment Analysis / Opinion Mining	0.679
66	Machine Translation (MT)	0.655
67	Neural Networks	0.640

Table 2. Top Skills in Each Skill Cluster in the Burning Glass Job Posting Data

This table reports the top five skills required by the largest number of job postings in each skill cluster in the Burning Glass Job Posting Data.

Administration	**Analysis**	**Business**	**Customer Service**	**Engineering**	**Finance**	**Health Care**
Scheduling	Data Analysis	Project Management	Customer Service	Mechanical Engineering	Budgeting	Patient Care
Administrative Support	Data Collection	Staff Management	Customer Contact	AutoCAD	Accounting	Cardiopulmonary Resuscitation (CPR)
Data Entry	Business Intelligence	Quality Assurance and Control	Basic Mathematics	Computer Engineering	Customer Billing	Lifting Ability
Appointment Setting	SAS	Supervisory Skills	Cash Handling	Simulation	Financial Analysis	Treatment Planning
Record Keeping	Statistics	Business Process	Customer Checkout	Civil Engineering	Financial Reporting	Advanced Cardiac Life Support

Human Resources	**Information Technology**	**Legal**	**Marketing**	**Sales**	**Science**	**Supply Chain**
Occupational Health and Safety	Microsoft Office	Legal Compliance	Marketing	Sales	Chemistry	Store Management
Onboarding	Microsoft Powerpoint	Litigation	Social Media	Product Sales	Biology	Purchasing
Recruiting	SQL	Government Regulations	Packaging	Merchandising	Physics	Forklift Operation
Employee Training	Java	Legal Documentation	Client Base Retention	Business Development	Experiments	Procurement
Personal Protective Equipment	Software Development	Criminal Justice	Facebook	Sales Goals	Laboratory Testing	Inventory Management

Agriculture	**Construction**	**Design**	**Economics**	**Education**	**Utilities**	**Environment**
Snow Removal	Estimating	Adobe Photoshop	Economics	Teaching	Natural Gas	HAZMAT
Lawn Care	Carpentry	Microsoft Visio	Public administration	Training Programs	Energy Management	Hazardous Waste
Fertilizers	Cost Estimation	Graphic Design	Economic Development	Training Materials	Power Distribution	Environmental Science
Agronomy	Construction Management	Adobe Indesign	Social Studies	Technical Training	Power Generation	Water Treatment
Agribusiness	Interior Design	Adobe Acrobat	Policy Analysis	Special Education	Energy Efficiency	Natural Resources

Industry Knowledge	**Maintenance**	**Manufacturing**	**Media**	**Personal Care**	**Public Safety**	**Religion**
Retail Industry Knowledge	Hand Tools	Product Development	Journalism	Cooking	Asset Protection	Youth Ministry
Information Technology Industry Knowledge	Plumbing	Machinery	Music	Food Safety	Surveillance	Student Ministry
Biotechnology	Predictive / Preventative Maintenance	Welding	Preparing Proposals	Child Care	Loss Control / Prevention	Children's Ministry
Industrial Engineering Industry Expertise	HVAC	Six Sigma	Proposal Writing	Food Preparation	Handling of Crisis	Family Ministry
Asset Management Industry Knowledge	Schematic Diagrams	Manufacturing Processes	Content Management	Food Service Experience	Emergency Services	Religious Education

Table 3. Summary Statistics

This table reports summary statistics for the sample of firms in our baseline regressions. All changes in variables are computed over 2010–2018. For each variable, we report the number of observations, the mean, the standard deviation, the median, and 1st, 5th, 10th, 25th, 75th, 90th, 95th, and 99th percentiles. The sample includes Compustat firms (in non-tech sectors) between 2010 and 2018.

Variable Name	**N**	**Mean**	**Std. Deviation**	**p1**	**p5**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**	**p99**
Change in share of AI workers	1218	.00079	.0025	-.0028	-.00028	0	0	0	.0005	.0021	.0044	.016
Change in share of workers with low seniority	1218	.0018	.055	-.13	-.084	-.065	-.029	-.00065	.028	.067	.1	.16
Change in share of workers with medium seniority	1218	.043	.044	-.08	-.031	-.0096	.02	.044	.068	.095	.11	.16
Change in share of workers with high seniority	1218	-.045	.033	-.16	-.11	-.088	-.059	-.04	-.023	-.01	-.0051	.015
Change in share of workers with college degree	1218	.062	.18	-.43	-.11	-.063	-.017	.031	.1	.21	.33	.97
Change in share of workers with master degree	1218	-.0012	.096	-.34	-.13	-.072	-.029	-.0054	.023	.082	.14	.35
Change in share of workers with doctoral degree	1218	.0014	.023	-.084	-.026	-.015	-.006	-.00047	.0047	.02	.042	.11
Change in share of workers without college degree	1218	-.063	.26	-1.3	-.46	-.31	-.13	-.025	.038	.13	.25	.83
Change in share of workers with STEM major	1216	.074	.12	-.33	-.09	-.036	.014	.054	.12	.23	.3	.53
Change in share of workers with social science major	1216	.049	.12	-.36	-.13	-.068	-.0047	.041	.096	.19	.26	.51
Change in share of workers with fine arts major	1216	.0019	.03	-.12	-.043	-.024	-.0071	.00025	.011	.03	.048	.13
Change in share of workers with humanities major	1216	.0054	.038	-.099	-.045	-.028	-.0096	.00082	.016	.041	.067	.19
Change in share of workers with medicine major	1216	.013	.033	-.063	-.019	-.0058	0	.0048	.017	.044	.074	.19
Change in average number of years of education (Burning Glass)	1060	-3.6	3.2	-14	-10	-8.4	-4.9	-2.7	-1.4	-.58	-.11	1.1
Change in average number of years of experience (Burning Glass)	1059	-.3	1.4	-5.5	-2.6	-1.9	-.94	-.2	.47	1.3	1.9	3
Change in share of job postings with administration skill	1099	.0088	.049	-.19	-.061	-.038	-.011	.0062	.029	.061	.088	.17
Change in share of job postings with analysis skill	1099	.0025	.018	-.076	-.024	-.013	-.0022	.0019	.0098	.021	.029	.057
Change in share of job postings with business skill	1099	-.0037	.07	-.29	-.12	-.079	-.034	.0022	.033	.072	.097	.16
Change in share of job postings with customer service skill	1099	.0067	.069	-.26	-.11	-.051	-.012	.0053	.029	.075	.12	.23
Change in share of job postings with engineering skill	1099	-.011	.052	-.31	-.11	-.05	-.01	0	.0053	.019	.035	.081
Change in share of job postings with finance skill	1099	-.011	.085	-.35	-.17	-.093	-.036	-.0031	.026	.069	.1	.22
Change in share of job postings with healthcare skill	1099	.0035	.053	-.23	-.07	-.029	-.0035	.0019	.012	.044	.084	.21
Change in share of job postings with HR skill	1099	.0062	.034	-.15	-.044	-.023	-.0039	.0059	.02	.039	.057	.12
Change in share of job postings with IT skill	1099	-.0073	.1	-.42	-.19	-.12	-.05	.0028	.045	.11	.14	.24
Change in share of job postings with legal skill	1099	.0012	.022	-.097	-.028	-.013	-.0036	.00059	.006	.018	.032	.095
Change in share of job postings with marketing skill	1099	.00085	.044	-.21	-.061	-.036	-.012	.0018	.018	.044	.065	.12
Change in share of job postings with sales skill	1099	-.0083	.1	-.36	-.19	-.11	-.039	-.002	.026	.083	.17	.32
Change in share of job postings with science skill	1099	-.0061	.041	-.27	-.053	-.025	-.0026	0	.0027	.011	.024	.1
Change in share of job postings with supply chain skill	1099	.013	.057	-.2	-.076	-.036	-.0057	.0079	.033	.08	.11	.22
Change in share of job postings with agriculture skill	1099	.00028	.0024	-.0084	-.00052	-.000048	0	0	7.4e-06	.00081	.0024	.016
Change in share of job postings with construction skill	1099	.0024	.016	-.065	-.014	-.0067	-.00099	.00031	.0045	.014	.026	.074
Change in share of job postings with design skill	1099	-.0015	.016	-.089	-.026	-.014	-.0041	.00013	.0042	.011	.017	.041
Change in share of job postings with economics skill	1099	.00039	.0044	-.019	-.0053	-.0022	-7.9e-06	.000014	.001	.0034	.0062	.02
Change in share of job postings with education skill	1099	.0005	.017	-.08	-.02	-.011	-.0033	.00052	.005	.012	.02	.067
Change in share of job postings with utilities skill	1099	-.002	.017	-.11	-.021	-.0058	-.00014	0	.00055	.0035	.01	.046
Change in share of job postings with environment skill	1099	.00033	.017	-.09	-.017	-.0055	-.00016	0	.0021	.0097	.018	.068
Change in share of job postings with industry knowledge skill	1099	-.0027	.039	-.16	-.076	-.037	-.012	0	.01	.027	.055	.14
Change in share of job postings with maintenance skill	1099	.013	.053	-.2	-.053	-.023	-.0029	.003	.026	.072	.11	.19
Change in share of job postings with manufacturing skill	1099	.0044	.044	-.19	-.061	-.031	-.0064	.001	.015	.05	.087	.15
Change in share of job postings with media skill	1099	.00046	.011	-.046	-.014	-.0091	-.0022	.00028	.0038	.0091	.016	.044
Change in share of job postings with personal care skill	1099	.0026	.023	-.084	-.01	-.0013	0	0	.00039	.0079	.025	.13
Change in share of job postings with public safety skill	1099	.000035	.0071	-.033	-.01	-.0032	-.000091	0	.0013	.0045	.008	.026

Table 4. Initial Worker Composition and AI Investments

This table reports the coefficients from regressions of cross-sectional changes in AI investments by U.S. public firms (in non-tech sectors) from 2010 to 2018 on the following ex-ante firm characteristics measured in 2010: share of workers in each seniority level in column 1, share of workers in each education level in column 2, and share of workers in each major (based on highest degree earned) in column 3. Column 4 include all firm characteristics in columns 1 to 3. The dependent variable is the growth in the share of AI workers from 2010 to 2018 using the resume data from Cognism. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. The dependent variable is normalized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share of AI Workers 2010-2018			
	(1)	(2)	(3)	(4)
Share of Workers with Low Seniority, 2010	-0.211			-0.322
	(0.393)			(0.396)
Share of Workers with Medium Seniority, 2010	-0.443			-0.127
	(0.407)			(0.414)
Share of Workers with College Degree, 2010		-0.489**		-0.327
		(0.232)		(0.263)
Share of Workers with Master Degree, 2010		0.891**		0.515
		(0.402)		(0.320)
Share of Workers with Doctor Degree, 2010		1.766**		2.429**
		(0.819)		(1.124)
Share of Workers with STEM Major, 2010			1.287***	1.000***
			(0.358)	(0.256)
Share of Workers with Social Science Major, 2010			0.310	0.288
			(0.371)	(0.278)
Share of Workers with Fine Arts Major, 2010			0.559	0.632
			(0.688)	(0.798)
Share of Workers with Humanities Major, 2010			3.074***	1.671
			(0.705)	(1.089)
Share of Workers with Medicine Major, 2010			0.499**	-0.314
			(0.227)	(0.423)
Industry Sector FE	Y	Y	Y	Y
Adj R-Squared	0.096	0.134	0.142	0.166
Observations	1,218	1,218	1,216	1,216

Table 5. AI Investments and Workers' Seniority Levels

This table reports the coefficients from long-differences regressions of the change in the share of workers in each seniority level from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The independent variable is the growth in the share of AI workers from 2010 to 2018 based on the Cognism resume data, standardized to mean zero and standard deviation of one. The dependent variables are the changes in the share of workers in each seniority level (low in columns 1 and 2; medium in columns 2 and 4; and high in columns 5 and 6) in the Cognism resume data. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of jobs, log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share Seniority Low		Δ Share Seniority Middle		Δ Share Seniority High	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.015***	0.016***	-0.007***	-0.008***	-0.007**	-0.008**
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Industry Sector FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.175	0.335	0.170	0.233	0.170	0.314
Observations	1,218	1,218	1,218	1,218	1,218	1,218

Table 6. AI Investments and Workers' Education Levels

This table reports the coefficients from long-differences regressions of the change in the share of workers in each highest education level from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The independent variable is the growth in the share of AI workers from 2010 to 2018 based on the Cognism resume data, standardized to mean zero and standard deviation of one. The dependent variables are measured using the Cognism resume data and represent the changes in the share of workers whose maximal attainment is a college degree in columns 1 and 2, the share of employees whose maximal attainment is a masters degree in columns 3 and 4, the share of employees with doctoral degrees in columns 5 and 6, and the share of employees with no college degree in columns 7 and 8. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of jobs, log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share College		Δ Share Master		Δ Share Doctoral		Δ Share No College	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.033***	0.037***	0.027***	0.029***	0.007***	0.006***	-0.068***	-0.073***
	(0.012)	(0.010)	(0.004)	(0.004)	(0.001)	(0.001)	(0.014)	(0.014)
Industry Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.099	0.198	0.107	0.217	0.155	0.210	0.115	0.214
Observations	1,218	1,218	1,218	1,218	1,218	1,218	1,218	1,218

Table 7. AI Investments and Required Education and Experience in the Job Postings Data

This table reports the coefficients from long-differences regressions of the change in the average required education and experience of from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The independent variable is the growth in the share of AI workers from 2010 to 2018 based on the Cognism resume data, standardized to mean zero and standard deviation of one. The dependent variables are the average required years of education in the Burning Glass job postings data in columns 1 and 2, and average required years of experience in the Burning Glass job postings data in columns 3 and 4. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of jobs, log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Years of Education		Δ Years of Experience	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.476**	0.516**	0.137*	0.061
	(0.204)	(0.217)	(0.072)	(0.078)
Industry Sector FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.397	0.458	0.161	0.235
Observations	1,060	1,060	1,059	1,059

Table 8. AI Investments and Workers' Majors

This table reports the coefficients from long-differences regressions of the change in the share of workers in each major from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are the share of employees whose most recent degree was in a STEM field in columns 1 and 2, the share of employees whose last degree was in social science in columns 3 and 4, the share of employees whose most recent degree was in fine arts in columns 5 and 6, the share of employees whose last degree was in humanities in columns 7 and 8, and the share of employees whose last degree was in medicine in columns 9 and 10. The majors are mutually exclusive; for each worker, we record the major of the most recent degree earned. STEM includes engineering (e.g., electrical, chemical, mechanical), physical sciences (e.g., math, physics, chemistry, computer science, statistics), and biological sciences (e.g., biology, pharmacology). The independent variable is the growth in the share of AI workers from 2010 to 2018 based on the Cognism resume data, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of jobs, log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share STEM		Δ Share Social Science		Δ Share Fine Arts		Δ Share Humanities		Δ Share Medicine	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.030***	0.029***	-0.011***	-0.007**	-0.003	-0.002	0.001	0.000	-0.002**	-0.003**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Industry Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.179	0.225	0.111	0.186	0.140	0.192	0.219	0.242	0.161	0.217
Observations	1,216	1,216	1,216	1,216	1,216	1,216	1,216	1,216	1,216	1,216

Table 9. AI Investments and Required Skills in the Job Postings Data

This table reports the coefficients from long-differences regressions of the change in the share of job postings requiring each skill cluster from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are the change in the average share of required skills in each skill cluster across all the job postings of the firm. The independent variable is the growth in the share of AI workers from 2010 to 2018 based on the Cognism resume data, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of jobs, log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share of Jobs w/ Administration Skill		Δ Share of Jobs w/ Analysis Skill		Δ Share of Jobs w/ Business Skill		Δ Share of Jobs w/ Customer Service Skill		Δ Share of Jobs w/ Engineering Skill		Δ Share of Jobs w/ Finance Skill		Δ Share of Jobs w/ Healthcare Skill	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Δ Share AI Workers	-0.001	-0.000	0.005***	0.004***	0.001	-0.003	-0.006	0.004	-0.000	-0.002	-0.007	-0.011**	-0.003	-0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)	(0.005)	(0.006)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.004)
Industry Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.062	0.094	0.264	0.306	0.094	0.146	0.222	0.349	0.038	0.123	0.059	0.178	0.046	0.100
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099

	Δ Share of Jobs w/ HR Skill		Δ Share of Jobs w/ IT Skill		Δ Share of Jobs w/ Legal Skill		Δ Share of Jobs w/ Marketing Skill		Δ Share of Jobs w/ Sales Skill		Δ Share of Jobs w/ Science Skill		Δ Share of Jobs w/ Supply Chain Skill	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Δ Share AI Workers	0.001	-0.000	0.016**	0.012*	-0.001	-0.000	0.003*	0.001	0.004	0.008	-0.000	-0.001	-0.006***	-0.002
	(0.001)	(0.002)	(0.007)	(0.007)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.006)	(0.001)	(0.001)	(0.002)	(0.003)
Industry Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.057	0.105	0.227	0.271	0.034	0.119	0.016	0.066	0.332	0.386	0.107	0.141	0.069	0.145
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099

	Δ Share of Jobs w/ Agriculture Skill		Δ Share of Jobs w/ Construction Skill		Δ Share of Jobs w/ Design Skill		Δ Share of Jobs w/ Economics Skill		Δ Share of Jobs w/ Education Skill		Δ Share of Jobs w/ Utilities Skill		Δ Share of Jobs w/ Environment Skill	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Δ Share AI Workers	-0.000	-0.000*	-0.001	-0.000	-0.001	-0.002	0.000	0.000	-0.001	-0.002*	-0.001	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.074	0.107	0.055	0.083	0.169	0.352	0.081	0.176	0.068	0.103	0.023	0.081	0.181	0.192
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099

	Δ Share of Jobs w/ Industry Knowledge Skill		Δ Share of Jobs w/ Maintenance Skill		Δ Share of Jobs w/ Manufacturing Skill		Δ Share of Jobs w/ Media Skill		Δ Share of Jobs w/ Personal Care Skill		Δ Share of Jobs w/ Public Safety Skill	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	-0.001	0.002	-0.007***	-0.006***	-0.002*	-0.002	0.001	0.001*	0.001	-0.000	-0.000	0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
Industry Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.117	0.166	0.121	0.168	-0.002	0.028	0.099	0.108	0.161	0.239	0.154	0.248
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099