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Abstract

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JEL Classification: N/A

Keywords: artificial intelligence, Machine Learning, Wage Premium, technology diffusion

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January 15, 2020

Abstract

We document a dramatic increase in the demand for AI skills in online job postings over the period 2010-2019. The demand for AI skills is highest in IT occupations, followed by architecture/engineering, life/physical/social sciences, and management. The sectors with the highest demand for AI are information, professional services, and finance. At the firm level, higher demand for AI skills is associated in the cross-section with larger market capitalization, higher cash holdings, and higher investments in R&D. We also document a large wage premium for job postings that require AI skills, as well as a wage premium for non-AI vacancies posted by firms with a high share of AI vacancies. Interestingly, managerial occupations have the highest wage premium for AI skills.

Keywords: artificial intelligence; machine learning; wage premium; technology diffusion

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1 Introduction

With most developed economies facing declining productivity growth and stable or shrinking working-age populations, new technologies that offer the potential to increase productivity are of immense interest to economists and policy makers. Artificial Intelligence (AI) is possibly the most promising technology currently in development and has potential applications across a wide range of industries and functions. While it offers the possibility of significantly higher productivity and job creation, it also makes it possible simply to replace humans and reduce costs (Acemoglu and Restrepo, 2019), leading potentially to lower labor share, increased inequality (Acemoglu and Restrepo, 2018*b*), and disruptions in many industries (Mateos-Garcia, 2019). Of great importance then is to understand the demand for AI skills in the labor market and whether AI is a "general purpose technology", a class of technologies with applications across industries and functions that are key drivers of innovation and economic growth (Bresnahan and Trajtenberg, 1995). We are still far from understanding the future impact of AI technology, but developing a better understanding of the adoption of AI across various spheres of economic activity is a step towards answering the question of how AI will impact the economy, either as a driver for a higher productivity and job creation or for a larger replacement of human labor and increased inequality.

In this paper, we study the diffusion of AI across occupations, firms, industries, and regions. Our first goal is to understand which firms are demanding AI skills and then whether differences in demand for AI can explain pay differentials across firms and labor markets. We can track the diffusion of AI in the U.S. using the online job vacancies database collected by the Burning Glass Technologies (BGT) that contains nearly a universe of online job postings. We measure the demand for AI skills as the number of vacancies requiring at least one AI-related skill. BGT data allow us to follow the hiring of AI specialists across industries, regions, occupations, and even job titles. BGT data is one of the most comprehensive databases of job vacancies in the U.S. and it has been used in multiple studies (e.g., Hershbein and Kahn, 2018; Modestino, Shoag and Ballance, 2019, 2016; Deming and Kahn, 2018) to analyse skill demand and labor outcomes in various labor markets.

We begin by documenting that firms hire (or strive to hire) more employees with AI-related skills, especially in the last three-four years. The rising trend is not surprising given the growing attention towards AI technology, and a sharp rise of demand for AI specialists in the last three years shows that the demand is still gaining momentum. We further show significant wage premia for AI skills across industries and occupations. We also find wage premia for non-AI-related positions at companies that are also looking for AI skills compared to similar positions at companies not looking to hire for AI skills.

The results presented in the paper thus provide one of the first aggregate pieces of evidence on the diffusion of AI technology that vary widely across firms and labor markets and document a substantial wage premium for AI skills and the change in the occupation tasks. Overall, our findings are consistent with, though not fully determinative of, AI being a "general purpose technology" that is "characterized by the potential for pervasive use in a wide range of sectors and by their technological dynamism" (Bresnahan and Trajtenberg 1995, p. 84; see also Goldfarb, Taska and Teodoridis 2019) and thus suggest that AI is likely to be a driver of significant transformations in the labor market over the next decades. These results can inform policymakers making decisions to ensure future employment and workers deciding about investment in their human capital that is necessary to fit the profile of the employee of the future.

Our paper primarily contributes to the literature stream analysing the effect of new technologies on productivity and labor market outcomes. This stream of research is motivated by the concerns that new technologies can displace labor. Autor, Levy and Murnane (2003) found that an increase in computer capital is associated with a reduced labor input of routine cognitive and routine manual tasks and an increased labor input of non-routine cognitive tasks. Acemoglu and Restrepo (2018*b*) developed a conceptual framework in which machines replace human labor and showed why automation can lead to a reduced labor share, employment, and wages. Other conceptual work on labor displacement in the result of automation includes Acemoglu and Autor (2011), Brynjolfsson and McAfee (2014), Benzell et al. (2015), and Acemoglu and Restrepo (2018*a*). Dillender and Forsythe (2019) showed that technology adopted in office, administrative, and support (OAS) occupations leads to a positive effect on employment and wages for the overall population but with wage losses for non-OAS workers. Autor et al. (2019) provided evidence that changes in the nature of work due to automation and international trade have been especially disruptive for jobs with non-college occupational skills and thus lead to a higher polarization of urban labor markets. Empirical evidence on the impact of AI on labor and productivity is still limited. Felten, Raj and Seamans (2019) provided evidence about the effect of advances across nine AI applications on wages and employment. They found that exposure to AI has no significant relationship with employment growth, but there is a positive correlation between AI and wage growth. Tambe et al. (2019) and Rock (2019) see no evidence that investments in AI increased firms' productivity, even though there is a positive association between AI and firm market values.

We also contribute to the literature analysing evolution in the demand for workers with different skills. Caroli and Van Reenen (2001) showed that organizational changes reduce the demand for unskilled workers. MacCrory et al. (2014) identified that over time occupations demand fewer skills that compete with machines and more skills that complement machines. Modestino, Shoag and Ballance (2019) found an upskilling effect during the Great Recession, especially in states, occupations, and years that had a larger increase in available workers supply. Hershbein and Kahn (2018) found that skill requirements in job postings increase more in MSAs that suffered larger employment shocks, and the upskilling mostly occurred in cognitive-routine jobs while manual-routine jobs were displaced by machines. Modestino, Shoag and Ballance (2016) also identified the opposite effect, downskilling, in the period of job market recovery after the crisis and showed a causal negative link between the labor market supply and vacancies selectivity. Deming and Kahn (2018) studied skills demand for professionals across labor markets using the same data as us (BGT). The authors identified that demand for cognitive and social skills is complementary to the measures of employee pay and firm performance across local labor markets. Deming and Noray (2019) identified that a faster technological change in STEM jobs leads to a faster skills obsolescence and a lower productivity gains from on-the-job learning in the result.

This study also adds to the literature using online job vacancies data to analyse labor market outcomes. Kuhn and Shen (2012) used data from one of the largest online job board in China to study gender discrimination. CareerBuilder.com job board was used by Marinescu and Wolthoff (2016) and to analyse the explanatory power of jobs titles for education and work experience requirements, by Marinescu (2017) to analyse the effect of unemployment benefits on job applications, and by Azar, Marinescu and Steinbaum (2017) and to calculate labor market concentration for labor markets in the US. Rothwell (2014), Modestino, Shoag and Ballance (2019), Modestino, Shoag and Ballance (2016), Hershbein and Kahn (2018), Deming and Kahn (2018), Azar et al. (2018), Azar et al. (2019), Deming and Noray (2019), Dillender and Forsythe (2019) used BGT data in their studies.

2 AI skills in Online Job Postings

Our main data source is the online job postings database provided by Burning Glass Technologies, an employment analytics and labor market information firm. From January 2010 to July 2019, BGT data contain details on nearly 192.3 million vacancies, including information on job title, standard occupation classification (SOC) code, detailed skill requirements, name and industry of the employer, job location, and wage offered. This data has been used in a range of studies analysing skills requirements across firms and labor markets (e.g., Hershbein and Kahn, 2018; Modestino, Shoag and Ballance, 2019, 2016; Deming and Kahn, 2018).

Carnevale, Jayasundera and Repnikov (2014) conducted a comprehensive analysis of the BGT data accuracy and representativeness compared to the overall job market. The report concludes that BGT online job ads correlate strongly with job openings data in JOLTS and provides detailed employment demand in a timely manner. The authors warn though that BGT may overrepresent job openings for college graduates and for industries that demand high-skilled workers. As well, based on the analysis by Hershbein and Kahn (2018), the aggregate and industry trends of the number of vacancies in the BGT data are consistent with other sources of job vacancies data, in particular CPS, OES and JOLTS. Indeed, we should be cautious about interpreting results in occupations and industries employing less skilled workers, since the BGT data can underrepresent such vacancies. BGT data is based on postings and, therefore, does not represent the exact profile of the actual employment. However, given the detailed information and dynamic nature of the online job postings data, it provides a unique source of information which allows us to trace the spread of AI technology we are interested in.

We identify vacancies requiring AI-related skills based on skill taxonomy developed by the BGT and based on the classification of nearly 17,000 unique skills obtained from job postings, resumes, and other sources into non-overlapping categories. BGT's skill taxonomy development process is described in Burning Glass Technologies (2019). Goldfarb, Taska and Teodoridis (2019) use an identification of AI-related jobs that is similar to ours. Overall, BGT identifies AI-related skills based on the presence of words and phrases commonly associated with the knowledge of AI (e.g., artificial intelligence, machine vision, deep learning, image processing, speech recognition, etc.) and AI-related software/systems (e.g., IBM Watson, TensorFlow, Pybrain, Random Forests, ND4J, etc.) in skill requirements part of a job description. Our goal is to define AI skills in the most straight-forward and encompassing manner. Appendix Table A1 provides a complete list of skill requirements we use to identify vacancies demanding AI.

BGT data provides a detailed information about the profile of desired job candidates, including education, work experience, but most importantly a list of skills required from a potential employee. Job postings can be characterized by ten additional skills which the extant literature has identified as relevant to explain pay differences across labor markets and performance differences across firms by Deming and Kahn (2018). We use these skills as controls in the regression analysis of wages. To categorize skills in these ten groups, we use the detailed definitions of the skill groups from the Appendix of Deming and Noray (2019).

One of the strengths of BGT data is its granular skill description contained in each vacancy and its up-to-date job positing, which allows us to capture the transformation for automation from AI without knowing the precise technology each firm is using (Frank et al. (2019)). Hence, we can estimate the share of AI vacancies posted by employers through time and observe the extent of firms', occupations' and industries' AI technology implementation. Moreover, detailed skill requirements data is key to identify changes in job tasks that are affected by technology. For instance, we document the trend of rising demand for AI skills in traditionally non-IT occupations, such as Management, Business and Financial, and Architecture and Engineering occupations.

Our sample consists of all job vacancies excluding internships from 2010 until 2019 which encompasses a total of approximately 190.2 million vacancies from the overall data. Panel A of Table 1 presents summary statistics for the full sample of job postings used in the descriptive part of the analysis. AI skills are demanded in 0.4 percent of the total vacancies, while Software specific skills are demanded in 21 percent and Cognitive skills in 28 percent of the vacancies. Panel B displays the demanded skill sets only for the subset of AI job vacancies and we observe that the skill profile is titled towards Software skills (86 percent) and Cognitive (69 percent).

As part of our descriptive analysis of AI skills, we study firm characteristics associated with the likelihood of the employer demanding AI skills. We match our vacancies sample to Compustat data based on employer's name. We focus on the last three full years of data in order to capture the most recent association between firm characteristics and the demand for AI. We drop observations with missing or negative Total Assets and Sales resulting in 2,516 unique Compustat's GVKEYs that are matched to the BGT data in the 2016-2018 period. Panel C of Table 1 shows financial and operational characteristics of the firms in the Compustat-matched sample where each observation is at SOC occupation-MSA-firm-year level. All variables in Compustat are adjusted for inflation and winzorised at 1 and 99 percent levels. On average, 33 percent of firm-year observations in the Compustat-matched data demand AI skills, while only 1 percent of 6-digit SOC occupation-MSA-firm-year cells tend to hire AI specialists.

Panel D of Table 1 shows the characteristics of vacancies posted by employers matched with Compustat. The demand for AI skills is slightly larger compared to the full sample (about 0.7 percent of the matched vacancies), while Software specific skills are demanded in 23 percent of the matched vacancies and Cognitive skills in 36 percent of the cases.

3 AI Hiring Over Time

Figure 1 shows the evolution of the demand for AI skills over the period 2010-2019. The number of job postings that mention AI skills has grown dramatically over this period, both in absolute terms and as a proportion of the overall number of vacancies posted. The number of AI job postings has increased from 20.6 thousand in 2010 to 180.9 thousand in 2018, and based on the projection of the data available for the first seven months of 2019 can be expected to reach nearly 220 thousand annual vacancies offered by the end of 2019. The proportion of job postings requiring AI skills relative to the total number of posted vacancies grew four times over the period 2010-2019. AI share of vacancies increased from 0.18 percent in 2010 to 0.63 percent in 2018 and was 0.72 percent for the vacancies posted in the first seven months of 2019.

To check that this trend is not driven by the addition of AI-hiring firms to the dataset over time, we also looked at the demand for AI skills among only the firms that were present in the dataset every year of the 2010-2019 period. Figure A1 in Appendix shows the evolution over time, for this subset of firms, of both the number of vacancies requesting AI skills and the overall AI share. The increase in the share of postings requiring AI skills for this balanced panel of firms is similar to the full sample. Therefore, this trend is not driven by changes in the universe of firms through time.

It is important to benchmark the growth of AI skills positing them relative to other computer skills. Figures 2(a) and 2(b) show analogous charts of the trends in the number and share of job postings requiring general Computer skills and specialized Software skills over time. The share of job postings mentioning general Computer skills is relatively flat over the period 2010-2019, while the share of job postings mentioning specialized Software skills declined slightly over this period.

Finally, to get a sense of the most frequently demanded AI-related skills in vacancies, we plot the top 15 skills based on the last month of our data, July 2019. Figure 3 shows that “Machine learning” is the most frequent term in AI-related vacancies. As a subset of the artificial intelligence field, machine learning is used to build mathematical models based on large data sets in order to make predictions without explicitly programming the task and has a variety of applications in different settings. Other more specific machine learning skills such as "Deep Learning" and "Image Processing" are also at the top of the list. The second most common skill is simply “Artificial intelligence”. “Natural language processing” is the third most demanded skill, followed by “Deep learning”, and “Image processing”. Interestingly, “IBM Watson” is the only AI skill in the top-15 list that relates to a specific system and not a general skill category or a scripting language library, such as “Keras”. IBM Watson is the information search and analytics solution developed by IBM that has applications in many industries, including agriculture, health, and finance, among others.

4 Industries and Occupations with Highest AI Share

In this section we explore the presence of AI vacancies across different industries and occupations as a proxy for AI technology adoption. Figure 4 shows AI vacancies’ share in broad industry sectors defined by the 2-digit NAICS codes. As expected, the Information industry is the one demanding most AI skill, on average 2.2 percent of vacancies in 2019. Professional, Scientific, and Technical Services sector demands just below 2 percent and the next groups of industries are Finance and Insurance, Administrative and Support Services, Agriculture, Forestry, Fishing and Hunting, and Manufacturing – all around 1 percent. The share of AI vacancies increased substantially in most 2-digit industries, especially in the last three years, as was also shown by the AI share growth trend for the overall economy in Figure 1. That is, demand for AI skills is as well present across a wide array of industries: Mining, Educational Services, or Public Administration are displaying increasing demand for such skills.

Figure 5 shows AI vacancies share in 2-digit SOC occupations. Computer and Mathematical occupations group has the highest AI share with 4 percent of vacancies demanding AI. However, other occupations are also increasingly hiring AI skills. Architecture and Engineering occupations, Life, Physical, and Social Science occupations, Management occupations, and Legal occupations are among the top five occupation groups with the highest AI vacancies' share. Even occupations with almost zero AI share at the beginning of our period such as Protective Services or Farming, Forestry, and Fishing are also requiring AI skills by 2019.

These results are consistent with a few recent studies analysing the diffusion and potential impact of AI. Klinger, Mateos-Garcia and Stathoulopoulos (2018) documents a fast spread of deep learning, a core technique in AI, in many computer science subfields. Cockburn, Henderson and Stern (2018) in turn suggest that AI is likely to impact the economy by serving as a new method for innovation process and R&D, which is consistent with the rising demand for AI in Architecture and Engineering and Life, Physical, and Social Science occupations.

5 AI Hiring and Firm Characteristics

In the previous section, we have shown that AI skills are increasingly demanded across a wide array of occupations and industries. AI is becoming a sought after skill beyond Computer occupations or Information-based industries. Given the wide and fast-growing pace of AI skill demand across occupations and industries, we want to understand what type of firms are demanding AI skills.

We explore the relationship between the probability of a firm to search for AI specialists and its firm characteristics using a Compustat-matched sample of posted vacancies described in Panel C of Table 1. To use the variation in the requirements for AI skills across labor markets, we measure whether the firm is hiring AI in each 6-digit SOC-MSA labor market. We estimate the association between the probability to post vacancies demanding AI skills and firm financial and operational characteristics using the following regression model:

$$\mathrm{AI}_{ismt} = \beta_1 \text{Firm Characteristics}_{it} + \beta_2 \text{Log}(\text{Vacancies}_{ismt}) + \gamma_i + \delta_{sm} + \zeta_t + \varepsilon_{ismt}, \tag{1}$$

where AI is a dummy variable equal one if firm i posted at least one vacancy demanding AI skills in market sm in year t and zero otherwise, Firm Characteristics$_{it}$ is the vector of Compustat-based financial and operational characteristics of firm i in year t, Log(Vacancies$_{ismt}$) is logarithm of the total number of vacancies firm i posted in market sm in year t, and γ_i, δ_{sm}, and ζ_t are firm, market (6-digit SOC-MSA market), and year fixed effects, and ϵ_{ismt} is an error term.

Table 2 shows the results of the regression analysis using a linear probability model that allows us to use a rich set of fixed effects. The results in columns 1-3 show that, in the cross section, there is a positive association between firms' market capitalization, liquidity, and R&D expenditures over sales and the demand of firms for the AI skills via posted vacancies. There is also a negative association between the market-to-book ratio of firms and the demand for AI skills. These results are consistent across all specifications in columns 1-3 controlling for year, year and MSA, or year and 6-digit SOC occupation-MSA fixed effects. Figure 6 shows the evolution of AI share of vacancies by the groups of firms based on their size, R&D expenditure, and cash stock. The figures are consistent with the regression results – the largest firms, firms with positive R&D, and high-liquidity firms have the largest AI share during the whole analysed period. With time, however, the gap between the top and middle/bottom group is increasing.

There is some evidence (columns 1-2) that the firms with a higher number of employees and the ratio of property, plant, and equipment to assets are on average less likely to demand AI skills. However, the statistical significance of these two variables disappears with the inclusion of a higher number of controls (columns 3-4).

Our base results are shown in Column 3 which includes SOC-MSA fixed effects and allows us to interpret the associations within labor markets and across firms. As expected, the strongest associations are for large market capitalization firms that are R&D intense. A one standard deviation increase in R&D intensity is associated with a 0.41 percentage points increase in the probability to demand AI skills. This probability increase is economically meaningful, as it represents a 39 percent increase relative to the base probability that firm posts vacancies demanding AI skills in the SOC-MSA market in a specific year, which is 1.06 percent. For market capitalization a one standard deviation increase in logarithm of market capitalization is associated with a 0.54 percentage points increase in the probability that the firm demands AI skills. It represents a 50 percent increase in the probability. As well, cash rich firms display a positive association with AI skills demand. Cash to assets ratio is associated with a 0.17 percentage points or a 16 percent increase in the probability to demand AI skills.

To our surprise, market-to-book ratio has a negative and significant coefficient and, therefore, a one standard deviation increase is associated with a 14 percent lower probability to demand AI skills. Finally, it is worth noting that return on assets as a proxy for operational performance shows no statistically significant association with the probability to demand AI.

When we look into the effects within firm (column 4) we find that the start of demanding AI skills over time is associated with an increase in market-to-book ratio and R&D intensity. It is also inversely related to cash stock ratio. A one standard deviation increase in R&D intensity is associated with a 0.43 percentage points (40 percent) increase in probability that the firm starts demanding AI skills. A one standard deviation increase in market-to-book ratio of the firm is associated with a 0.22 percentage points (21 percent) higher probability that the firm starts posting vacancies demanding AI skills. Finally, a standard deviation increase in cash-to-assets ratio is associated with a 0.21 percentage points (20 percent) lower probability that the firm will start demanding AI skills.

Overall, in the specification with firm fixed effects, market-to-book ratio increase might suggest that the stock market values the start of hiring AI specialists that might proxy for the introduction or start of the development of AI systems. An increase in capital and R&D expenses relative to assets is consistent with the view that investments in AI can increase productivity only when accompanied by complementary investments in IT infrastructure, skills, and business processes. However, these relationships only show correlation and in reality can be driven by a common event affecting firm performance and the start of posting vacancies demanding AI skills.

6 The AI Wage Premium

We have shown that firms' large market capitalization, R&D intensity, and liquidity are positively correlated with the probability of demanding AI skills. As well, the data reflects that AI skills are increasingly demanded by a wide array of firms across sectors. Our next goal is to explore whether pay differentials across firms and labor markets can be explained by the differences in demand for AI. Do firms pay a premium for AI skills vis-a-vis other computer specific skills?

If jobs requiring AI skills are expected to be more productive with this new skill, then the vacancies will offer a significant wage premium for such a skill. As well, we may observe differences in AI skills premium across different occupations. For example, managers with AI knowledge might focus on the strategy of implementing AI solutions in their organization rather than programming these solutions. In contrast, employees in computer occupations with additional AI skills might be devoted to developing AI systems within the organizations. Thus, both occupations requiring AI might have different levels of complexity in terms of combining AI knowledge with other skills and can be expected to deliver differential benefits to the employer. Since we cannot observe production technologies in the organizations to help us identify which of these occupations is more productive, we must rely on employers preference for skills and the corresponding salaries. With the detailed vacancy description on skills and the offered salary we can illuminate the expected benefits from these hires.

We estimate wage premiums using standard wage regressions on employee skills and use job posting-level wage data from 2016 until 2018. We estimate the following regression:

$$\text{Log}(\text{Wage}_{vismt}) = \beta_1 \text{AI}_{vismt} + \beta_2 \text{Other Skills}_{vismt} + \gamma_i + \delta_{sm} + \zeta_t + \nu_{vismt}, \tag{2}$$

where $\log(\text{Wage})_{vismt}$ is the logarithm of salary offered in the job vacancy v posted by firm i in the market sm and year-month t, AI_{vismt} is the indicator variable equal one if the vacancy requires at least one AI-related skill, $\text{Other Skills}_{vismt}$ is the vector of ten indicator variables equal one if the vacancy requires one of the ten skills we use as controls following prior literature (Deming and Kahn, 2018) and zero otherwise, γ_i, δ_{sm}, and ζ_t are firm, market (6-digit SOC-MSA labor market), and year-month fixed effects, and ϵ_{vismt} is an error term.

Table 3 presents the estimated premia for AI and a set of skills that recent literature has deemed relevant (Deming and Kahn, 2018). We are interested in the AI skills vis-a-vis Software specific skills as well as Cognitive skills. Note that an array of fixed effects is added to specifications one by one. In the last column we add fixed effects for the standardized versions of job titles stated in the job vacancy posting.

Column 1 shows that AI skills represent a substantial premium of 51 percent for a vacancy demanding AI relative to the wages for jobs with no AI requirement but with a similar portfolio of other skills. In column 2 we include MSA fixed effects to account for the differences in wages due to the local cost of living and other unobserved regional factors. Within MSAs the premium persists. In column 3 we replace MSA fixed effects with MSA-occupation and industry fixed effects. This allows us to narrowly define labor markets and account for differences across industries. The AI wage premium is now 18 percent. This means that in the same 6-digit occupation and the same regional labor market, an employee with

AI skills is offered on average an 18 percent higher salary than a comparable employee with no such skills. We may want to benchmark this effect vis-a-vis Software specific skills, which offer on average an 8 percent premium. Column 4 adds firm fixed effects to account for constant firm characteristics within 6-digit occupation-MSA markets. Even when we control for unobserved firm characteristics, vacancies demanding AI skills offer an 11 percent higher salary than vacancies with no demand AI skills. The Software specific skills account for a 6 percent premium.

When we introduce job title fixed effects in column 5, the premium for AI decreases significantly and is equal to 5.3 percent over salaries for the same job titles in the same firms and labor markets but with no AI skill requirement. Therefore, the job title seems to account well for the skill requirements of the job and acts as a moderator variable in the relationship between the AI skills requirement and the wage.

It is noteworthy to compare the AI and Software skills premia to the more general Cognitive skills premium. Across specifications, Cognitive skills do display a positive premium, however it is much smaller. Accounting for MSA, SOC and firm effects, Cognitive skills deliver a 3.5 percent wage increase.

As a robustness check, we repeat the analysis of the wage differential for the sample of professional occupations with SOC codes 11-29 and 41-43 (not tabulated), used by Deming and Kahn (2018) and Deming and Noray (2019) in their analyses of the effect of skills on labor market outcomes. The sample decreases by 35-40 percent as the result of dropping non-professional occupations, but the magnitude and significance of the coefficients of interest do not change significantly and the results remain qualitatively the same. Thus, we conclude that the inclusion of non-professional job vacancies into the regression analysis does not affect our inference.

To further understand whether the perceived productivity of AI specialists differs across occupations, we run the analysis for the set of occupations that display a high demand for AI skills in Figure 5 - Computer and Mathematical occupations (SOC 15), Architecture and Engineering occupations (SOC 17), Life, Physical, and Social Science occupations (SOC 19), Management occupations (SOC 11), Legal occupations (SOC 23), and Business and Financial Operations (SOC 13). The main specification for this analysis accounts for time, SOC-MSA market and firm fixed effects to ensure we are comparing job vacancies within labor markets and that we control for (unobserved) firms characteristics. The results are presented in Table 4.

As expected, AI is very relevant for vacancies in Computer and Mathematical occupations (column

1), offering a 9.2 percent higher salary than similar jobs with no AI skill requirement. Note that within this occupation Software specific skills have a larger coefficient delivering a stronger premium than the AI skills. To our surprise, Management occupations (column 4) deliver the strongest AI skill premium: job postings for managers that demand AI skills offer 10.7 percent higher salary than job postings for managers that do not require such skills. However, the premium of Software specific skills is much smaller (only 3.5 percent) and is less relevant than Cognitive and Social skills.

Jobs in Architecture and Engineering occupations offer 4.8 percent premium, Life, Physical, and Social Science occupations a 7.7 percent, and Business and Financial Operations a 7.6 percent higher salary than similar jobs not requiring AI skills. Finally, the AI coefficient is insignificant for vacancies in Legal occupations.

Next, we explore premia across 2-digit NAICS industries with the highest share of AI vacancies (as in Figure 4. Table 5 presents the results for all occupations in the top six 2-digit NAICS industries: Information (NAICS 51), Professional, Scientific, and Technical Services (NAICS 54), Finance and Insurance (NAICS 52), Administrative and Support services (NAICS 56), Agriculture, Forestry, Fishing and Hunting (NAICS 11), and Manufacturing (NAICS 31-33).

The largest premium for AI skills is displayed in the Administrative and Support services sector which encompasses credit bureau, document management, call centers, and other business support type of organizations. In this sector, a vacancy demanding AI skills offers a 19.4 percent higher salary than a vacancy with no demand for AI. This sector has experienced the most sudden increase in demand for AI skills. Information industry and Finance and Insurance offer comparable 11.4 and 11 percent premium in the vacancies with AI skill requirements respectively. It is striking that for wages offered by Information and Finance and Insurance organizations Social skills do not have statistical significance.

Overall, these results are consistent with the results reached by Felten, Raj and Seamans (2019) who created a measure of AI Occupational Impact based on method proposed in Felten, Raj and Seamans (2018). The authors found that occupations affected by AI experience a small positive change in wages and no change in employment and that the positive correlation with wages is driven primarily by occupations with higher software skill requirements.

7 AI Skills and Non-AI Vacancy Wages

Our next goal is to explore whether the AI share of vacancies posted by the employer is associated with a salary differential for the rest of posted vacancies not requesting AI skills. For instance, demanding AI in job vacancies can signal a certain quality of the firm. As well, demanding AI can enable the creation of new tasks that increase demand for high-skilled jobs that may complement this technology.

We measure the AI share of vacancies for each employer-month and estimate a regression model similar to equation 2 substituting AI dummy variable for the employer-month level of AI share of vacancies. Our sample is now comprised of vacancies requesting non-AI skills. The results of this analysis are presented in Table 6.

Results in columns 1-3 show that the increase in the AI share of vacancies has a strong positive association with the wage level offered by non-AI vacancies. Columns 4 shows that the effect is present even after including firm fixed effects, even though the significance of the coefficient becomes weaker. This result suggests that firms that hire AI specialists also offer higher salaries in non-AI vacancies. However, when job title fixed effects are added to the specification, the statistical significance of the AI share disappears.

This evidence may suggest that firms that require AI are higher-paying in general. There is some evidence that after controlling for constant firm characteristics, a higher share of AI vacancies is associated with an increase in non-AI wages. This result is consistent with the view that new technologies can facilitate the creation of new tasks that increase the demand for high-skilled jobs that complement AI.

We find support to this view repeating this analysis for the subsamples of 2-digit occupations and industries. As shown in Table A2, the increase in the AI share of vacancies is associated with the increase in wages offered by non-AI vacancies in Computer and Mathematical, Management, and Business and Financial occupations. Results in Table A3 also show that the increase in AI share is positively correlated with the level of wages offered by non-AI vacancies in Professional, Scientific, and Technical Services and Administrative and Support Services. These results show that the complementarity of AI is not evenly distributed across occupations and sectors. However, so far we see the positive or no effect of the increase in the hiring of AI specialists on offered wages in non-AI jobs.

8 AI Skills and Average wages

It can be argued that salaries reported in the posted vacancies do not reflect the actual labor income. Therefore, we repeat the analysis relying on the median wage information for MSA-occupation markets provided by the Occupational Employment Statistics (OES) collected by the Bureau of Labor Statistics. The OES data is constructed based on a semi-annual mail survey of non-farm establishments. The OES survey collects information in every metropolitan and non-metropolitan area from establishments of varying sizes that represent all surveyed industries. These data, however, only allow us to analyse the relationship between the share of AI vacancies and wages at the 6-digit occupation-MSA market, and not at the individual firm level.

In this analysis, we closely follow existing literature (e.g., Deming and Kahn (2018)) and include two sets of controls. First set of controls includes MSA-level demographic characteristics from the American Community Survey (ACS) data[1], 4-digit SOC fixed effects, and the shares of vacancies in each of the 2-digit NAICS industries in the SOC-MSA market. A more detailed set of controls includes 6-digit SOC and MSA fixed effects and the 2-digit industries' shares. In all regressions, we also include the average years of education and experience required in the vacancies posted in the 6-digit SOC-MSA market. All regressions are weighted by the number of vacancies in the occupation-MSA market.

Table 7 presents the regression results for the period 2016-2017[2]. Columns 1 and 2 present results of regressions for the sample that includes all occupations. Market-level AI share has a positive association with the median wage in the market, even controlling for MSA and 6-digit occupation fixed effects. The magnitude of AI share coefficient in column 1 implies that a 1 percentage point increase in the AI share of vacancies is associated with a 0.55 percent higher median wage in the 6-digit SOC-MSA market. When we include more detailed controls (column 2), a 1 percentage point increase in AI share of vacancies is associated with a 0.27 percent higher median wage. Columns 3 and 4 show the results for the sample that includes only professional occupations, as in Deming and Kahn (2018). For professional occupations

[1]We include the share of Black, Asian, and Hispanic population, shares of population by educational attainment, shares of population by age groups, share of Female population, share of married population. We also include a dummy for whether MSA matched with the ACS data, and replace controls in unmatched observations with zeros.

[2]The most recent ACS data at the time of our analysis is available for 2017 and OES data – for May 2018. Thus, due to data availability, the analysed period is limited by 2017. We use wages reported in May 2018 and May 2017 as dependent variables, while explanatory variables are included as at 2017 and 2016 respectively. Thus, we assume that wages reported in May of each calendar year reflect hiring in the previous calendar year. Using wages that are contemporaneous to explanatory variables delivers similar results.

(column 3), the analogous increase in AI share is associated with 0.44 percent higher wages. The fact that most skill shares are insignificant in column 4 suggests that constant characteristics of MSA and 6-digit SOC occupations explain most variation in wages of professional occupations in the analysed period.

The results are robust to using mean 6-digit occupation-MSA wages instead of median wages. The effect is also in place when we use unweighted regressions. In unweighted regressions presented in Table A4 of Appendix, AI share has significant positive coefficient in all specifications. A 1 percentage point increase in AI share of vacancies is associated with 0.52 percent higher wages in specification with less detailed controls (column 1) and with 0.09 percent higher wages in specification with 6-digit SOC and MSA fixed effects (column 2). The coefficients are slightly lower when we focus on professional occupations in columns 3 and 4.

Overall, we find evidence that labor markets with higher wages demand more AI skills, even controlling for other skills and constant differences in pay between occupations and regions. Again, when AI share of vacancies is significant in the regressions, we find that it is associated with the highest wage premium compared to other skills.

9 Conclusion

Given the increasing importance of artificial intelligence (AI) for economic activity and the dearth of knowledge about its effects, we have examined the diffusion of AI through looking at the demand for AI-related skills in the labor market. We have used data from Burning Glass Technologies (BGT) consisting nearly of the universe of online job postings in the USA.

Our findings suggest a dramatic increase in the demand for AI skills. The number of positions requiring AI skills has increased ten-fold from 2010 to 2019 and four-fold as a share of all job postings. While a large proportion of the demand for AI skills is focused in information technology, professional services, finance, and manufacturing, the increase in demand is evident in most 2-digit NAICS industries. Likewise, demand for AI skills is concentrated in computer, engineering, and science occupations, but the increase is evident in a large number of 2-digit SOC occupations, including for instance farming, forestry, and fishing which at the beginning of the observation period had almost zero demand for AI skills.

We further find that there are clear differences between firms that are looking for AI skills and those that are not. In a cross-sectional analysis, firms with higher market values, higher R&D intensity, higher cash stock, and greater number of vacancies are likely to be looking for AI skills. In a given firm, we find that increases in capital and R&D intensity are associated with an increased likelihood of hiring for AI skills. This is consistent with AI increasing productivity when combined with complementary investments in infrastructure, skills, and processes.

Our results also indicate a clear wage premium for AI skills. For job postings with comparable other skills, the addition of AI skill requirement increases the wage by 51%. Controlling for local labor market conditions with occupation-MSA fixed effects reduces this premium to 18% and further controlling for firm and job title reduces it to 5.3%. This premium is substantially higher than for other skills in our analysis, being for instance more than twice as high as for other software skills. Within occupations, we find the highest premium in management occupations, suggesting that the ability to understand the impact of AI on broader aspects of the business carries a lot of value, comparable to general people management skills.

Comparing the wages of positions that do not require AI skills in companies that are also looking for AI skills with the wages for similar positions in companies that are not looking for AI skills, we find a significant wage premium in non-AI positions in companies that are looking for AI skills. This could be a signal of the quality of the firm and is also consistent with the AI enabling productivity gains in complementary positions.

Overall, our findings clearly indicate a dramatic increase in the recruitment of people with AI skills. Such recruitment appears to be taking place in high quality firms that invest R&D, are increasing in employment, and pay higher wages for other positions as well. In general, these findings are consistent with AI being a "general purpose technology" (Bresnahan and Trajtenberg, 1995; Goldfarb, Taska and Teodoridis, 2019) and give us at least a glimmer of hope that AI will improve productivity and create new opportunities.

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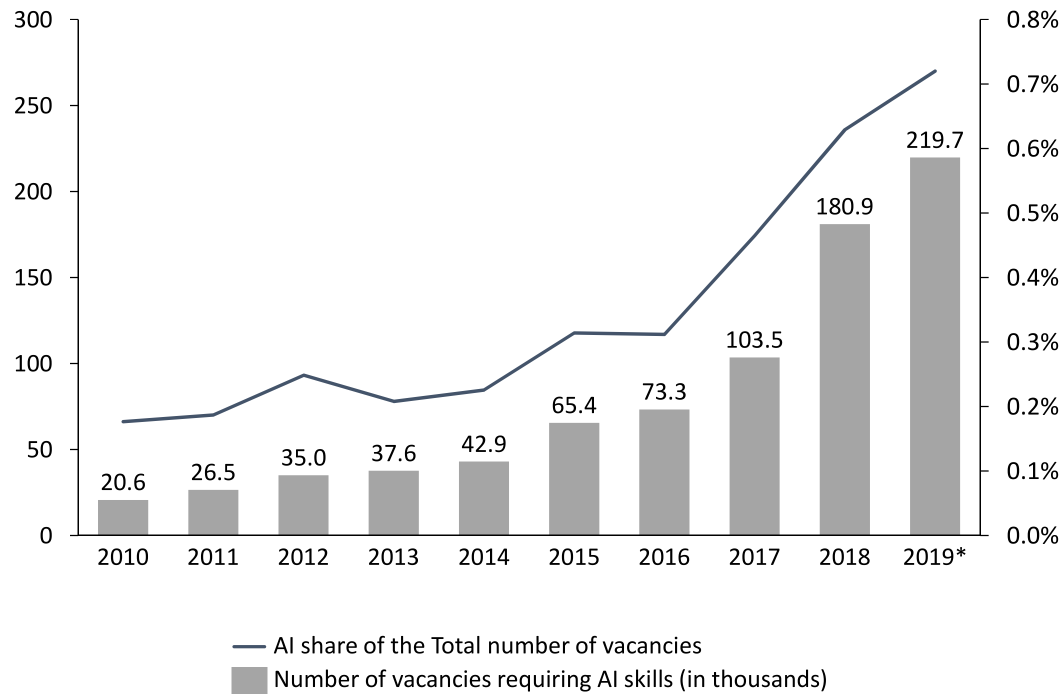
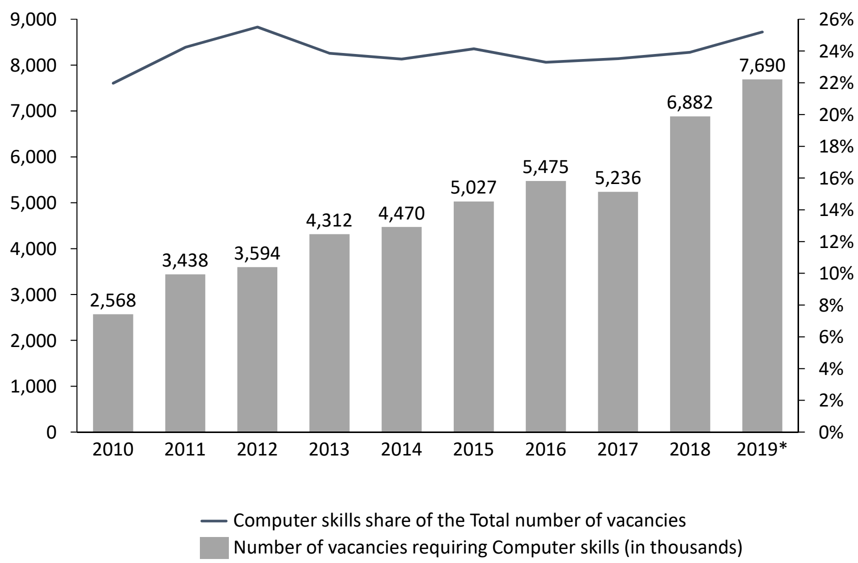
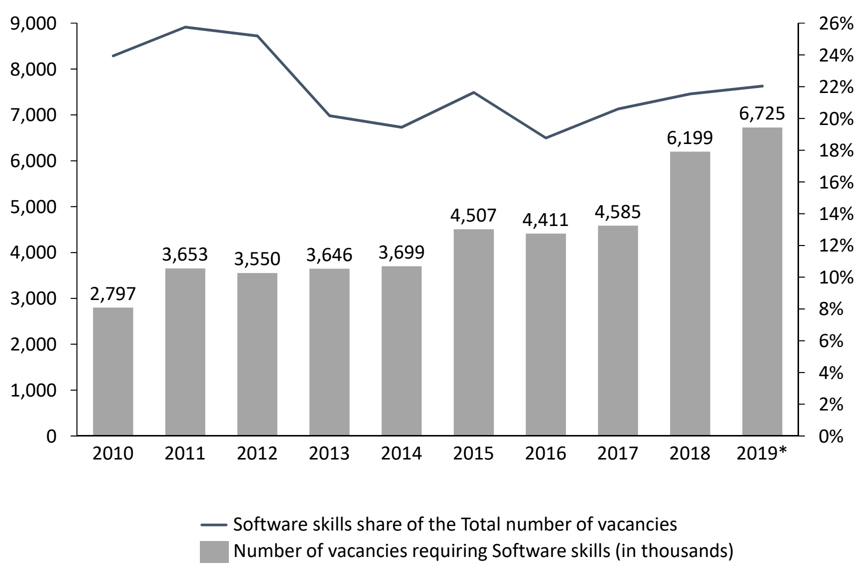


Figure 1. AI share of total hiring over time. The figure shows the number of vacancies requiring AI skills over time (bars) and the ratio of the number of vacancies requiring AI skills to the total number of vacancies (line). The total number of vacancies requiring AI in 2019 is a projection based on the annualized number of vacancies posted in January-July, 2019.



(a) Computer skills share of total number of vacancies over time.



(b) Software skills share of total number of vacancies over time.

Figure 2. Share of vacancies with Computer and specialized Software skills over time. The figure shows the number of vacancies requiring the analysed skills over time (bars) and the ratio of the number of vacancies requiring these skills to the total number of vacancies (line). The total number of vacancies requiring Computer/Software skills in 2019 is a projection based on the annualized number of vacancies posted in January-July, 2019.

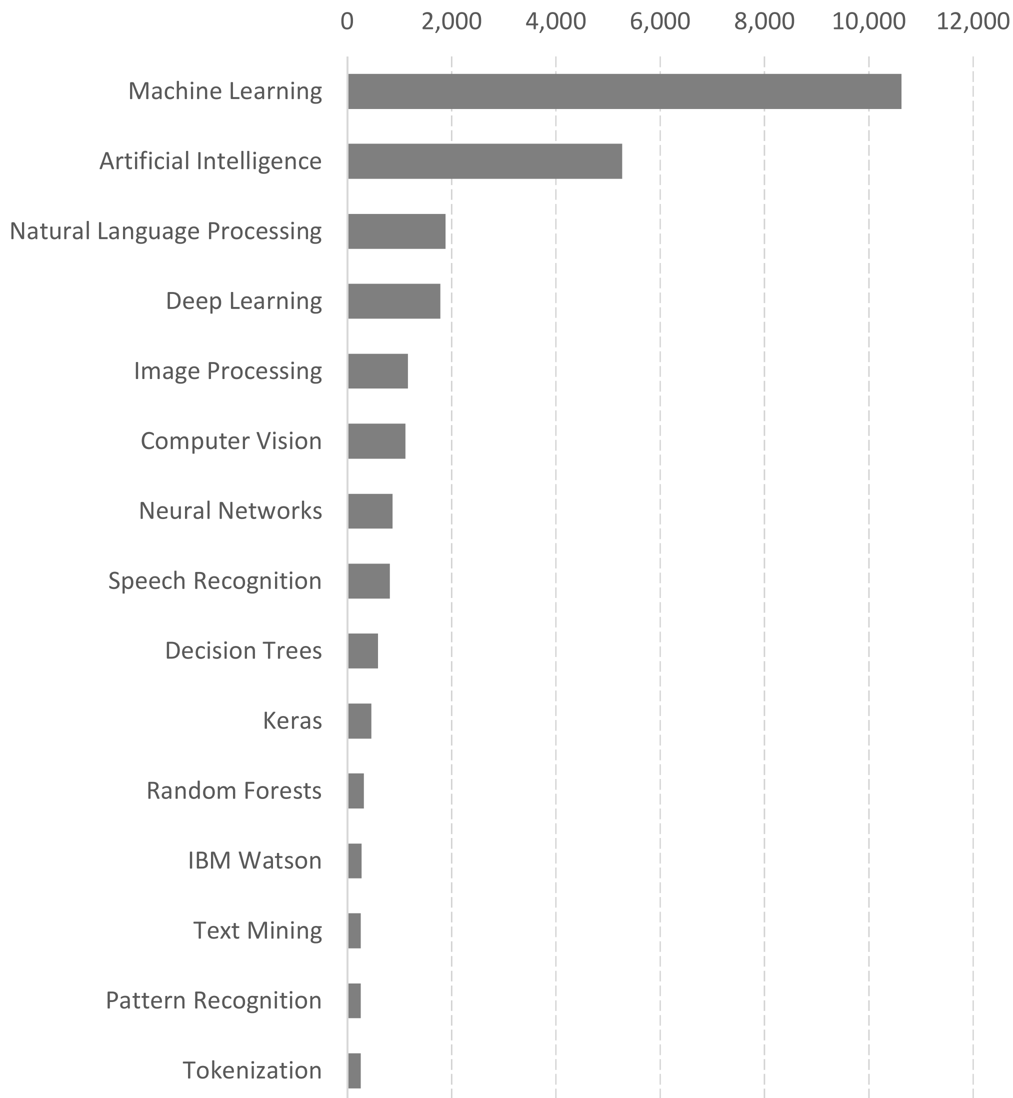


Figure 3. Most frequently required AI skills in online job postings in 2019m7. The figure shows the top 15 skills sorted by the frequency with which they are demanded in AI vacancies in the Burning Glass Technologies dataset in July of 2019.

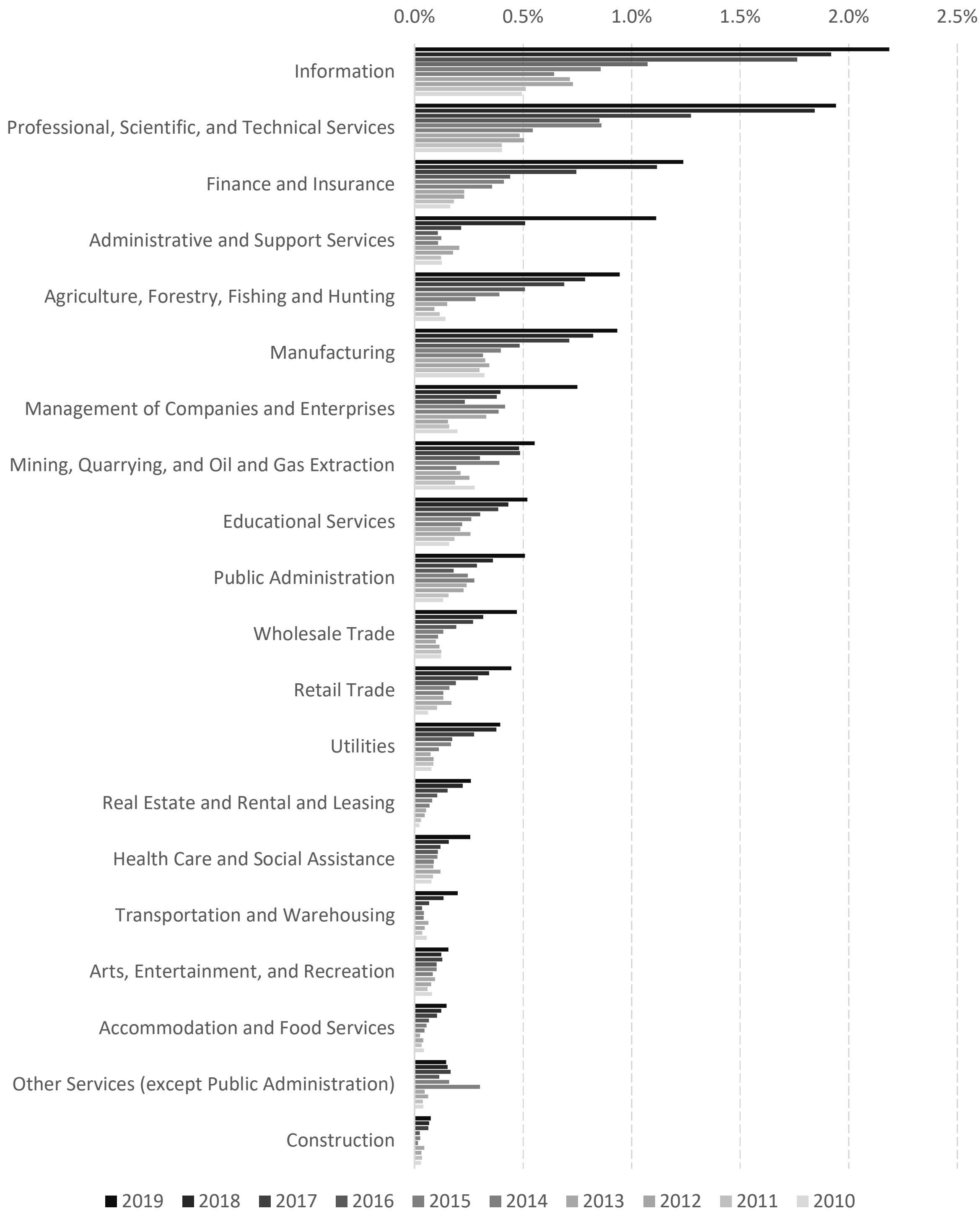
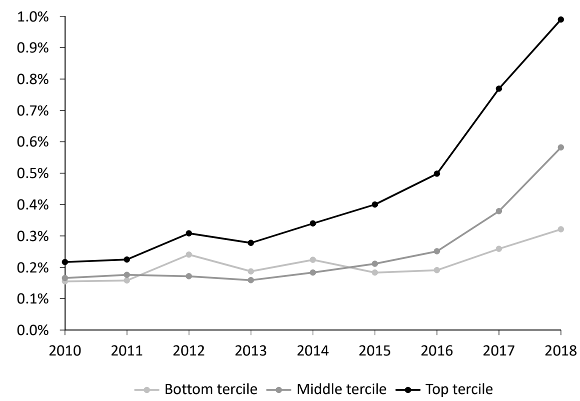
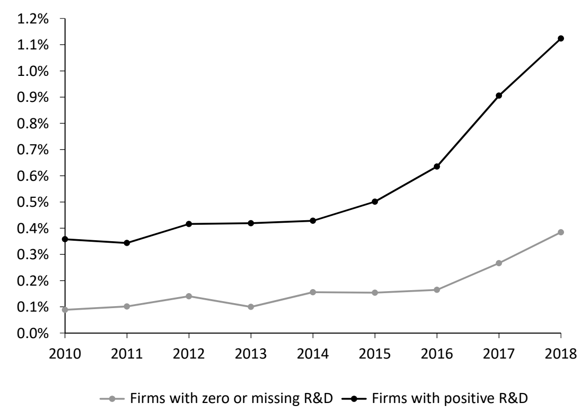


Figure 4. AI share by industry over time. The Figure shows the share of AI vacancies in the total number of vacancies by 2-digit NAICS industries in 2010-2019. Industries are ranked by the AI share in 2019. Data only includes job postings with non-missing 2-digit NAICS codes.

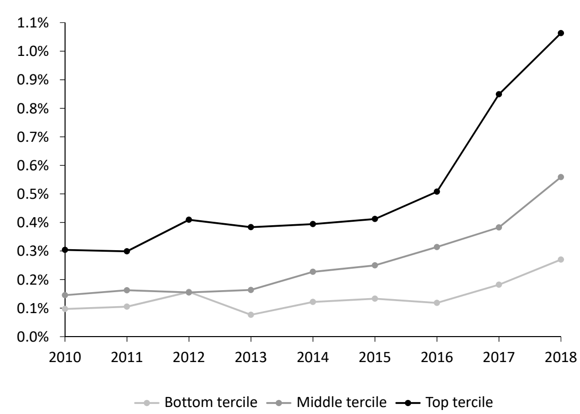
Figure 5. AI share by occupation over time. The Figure shows AI share of vacancies for 2-digit occupations (first two digits of SOC code) over 2010-2019. Occupations are ranked by the AI share in 2019. Data only includes job postings with a non-missing SOC occupation code.



(a) AI share by terciles of market capitalization.



(b) AI share by R&D expenses.



(c) AI share by terciles of cash-to-assets ratio.

Figure 6. Share of vacancies requiring AI skills by firm groups over time. Data source: Burning Glass Technologies merged with Compustat.

Table 1. Summary statistics.

(a) Panel A: Job vacancies data - Full sample, 2010-2019 period.
Data source: Burning Glass Technologies.

Variable	Obs.	Mean	Std.	Min	Max
Salary	33,822,194	57,306.91	42,721.65	10,004.80	350,000.00
AI	190,218,763	0.0038	0.0611	0	1
Software (specific)	190,218,763	0.2154	0.4111	0	1
Computer (general)	190,218,763	0.2391	0.4266	0	1
Cognitive	190,218,763	0.2826	0.4502	0	1
Social	190,218,763	0.3979	0.4895	0	1
Character	190,218,763	0.2039	0.4029	0	1
Writing	190,218,763	0.0510	0.2199	0	1
Customer service	190,218,763	0.3889	0.4875	0	1
Project management	190,218,763	0.0757	0.2646	0	1
People management	190,218,763	0.1371	0.3439	0	1
Financial	190,218,763	0.1524	0.3594	0	1

(b) Panel B: Job vacancies data - only AI jobs vacancies, 2010-2019 period.
Data source: Burning Glass Technologies.

Variable	Obs.	Mean	Std.	Min	Max
Salary	89,382	104,392.00	48,367.00	10,400.00	350,000.00
Software (specific)	713,858	0.8613	0.3457	0	1
Computer (general)	713,858	0.2824	0.4502	0	1
Cognitive	713,858	0.6943	0.4607	0	1
Social	713,858	0.5921	0.4914	0	1
Character	713,858	0.1970	0.3977	0	1
Writing	713,858	0.0845	0.2782	0	1
Customer service	713,858	0.2672	0.4425	0	1
Project management	713,858	0.1501	0.3572	0	1
People management	713,858	0.1766	0.3813	0	1
Financial	713,858	0.1404	0.3474	0	1

(c) Panel C: Firm characteristics - Compustat-matched sample , 2016-2018 period.
Sample includes observations with non-missing SOC code and MSA in BGT data and with non-missing financial information and 3-digit NAICS codes in Compustat. Data is at the MSA-6-digit SOC occupation-firm-year level.
Data source: Burning Glass Technologies merged with Compustat.

Variable	Obs.	Mean	Std.	Min	Max
AI dummy	1,760,385	0.0106	0.1022	0	1
Market Cap	1,760,385	34,295.24	72,004.68	0.06	996,790.70
Employment	1,760,385	95.7022	228.5110	0.0020	2,300.00
Market-to-Book	1,760,385	2.0551	1.2622	0.7600	8.6652
ROA	1,760,385	0.0461	0.0780	-0.2846	0.2429
Cash / Assets	1,760,385	0.1083	0.1206	0.0015	0.6210
Leverage	1,760,385	0.3314	0.2061	0	1.1183
R&D / Sales	1,760,385	0.0243	0.0550	0	0.3116
CAPEX / Sales	1,760,385	0.0509	0.0696	0.0025	0.5873
Overhead Share	1,760,385	0.2734	0.1924	0.0121	0.8739
PP&E / Assets	1,760,385	0.5210	0.3908	0.0208	1.7110
Vacancies	1,760,385	4.8149	19.6217	1	5,160

(d) Panel D: Job vacancies data - Compustat-matched sample, 2016-2018 period.
Sample includes observations with non-missing SOC code and MSA.
Data source: Burning Glass Technologies

Variable	Obs.	Mean	Std.	Min	Max
AI	8,476,043	0.0066	0.0809	0	1
Software (specific)	8,476,043	0.2292	0.4203	0	1
Computer (general)	8,476,043	0.2482	0.4320	0	1
Cognitive	8,476,043	0.3615	0.4804	0	1
Social	8,476,043	0.5115	0.4999	0	1
Character	8,476,043	0.2447	0.4299	0	1
Writing	8,476,043	0.0405	0.1971	0	1
Customer service	8,476,043	0.5723	0.4947	0	1
Project management	8,476,043	0.0872	0.2822	0	1
People management	8,476,043	0.1770	0.3816	0	1
Financial	8,476,043	0.1495	0.3565	0	1

Table 2. Regressions of AI Skill Demand on Firm Characteristics.
Estimation is for the period 2016-2018, and excludes internships. Standard errors are clustered by MSA, 6-digit SOC occupation, and 3-digit NAICS industry.
Data source: Burning Glass Technologies and Compustat

	Dependent Variable: AI Indicator			
	(1)	(2)	(3)	(4)
Log Market Cap	0.00368***	0.00350***	0.00274***	0.00110
	(0.00100)	(0.000985)	(0.000851)	(0.00107)
Log Employment	-0.00210***	-0.00163**	-0.000538	0.00315
	(0.000750)	(0.000683)	(0.000449)	(0.00232)
Market-to-Book	-0.00150***	-0.00146***	-0.00114***	0.00173**
	(0.000542)	(0.000519)	(0.000416)	(0.000841)
ROA	-0.00913	-0.00827	-0.00254	0.000332
	(0.00971)	(0.00953)	(0.00915)	(0.00557)
Cash/Assets	0.0241***	0.0199**	0.0145**	-0.0173***
	(0.00887)	(0.00766)	(0.00669)	(0.00522)
Leverage	0.00193	0.00217	0.00283	-0.00371
	(0.00257)	(0.00247)	(0.00259)	(0.00314)
R&D/Sales	0.163***	0.132***	0.0742***	0.0775*
	(0.0484)	(0.0366)	(0.0204)	(0.0400)
Capex/Sales	0.0147	0.0142	0.0145	0.00910
	(0.0107)	(0.0107)	(0.00946)	(0.0100)
Overhead Share	-0.00661	-0.00638	-0.00178	-0.00264
	(0.00587)	(0.00509)	(0.00378)	(0.00711)
PP&E/Assets	-0.00513**	-0.00428*	-0.00135	-0.000012
	(0.00237)	(0.00218)	(0.00157)	(0.00403)
Log Vacancies	0.0146***	0.0139***	0.0143***	0.0149***
	(0.00519)	(0.00506)	(0.00468)	(0.00472)
Observations	1,760,385	1,760,384	1,707,591	1,707,460
R-squared	0.034	0.040	0.185	0.206
Year FE	✓	✓	✓	✓
MSA FE		✓		
MSA $\times$ SOC FE			✓	✓
Firm FE				✓

Standard errors in parentheses clustered by MSA, SOC, and 3-digit NAICS
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Regressions of Log Wage on AI and Other Skills: All Occupations.
Estimation is for the period 2016-2019, and excludes internships. Standard errors are clustered by MSA, 6-digit SOC, and 3-digit NAICS. Data source: Burning Glass Technologies

	Dependent Variable: Log Wage				
	(1)	(2)	(3)	(4)	(5)
AI	0.413***	0.378***	0.164***	0.107***	0.0514***
	(0.0500)	(0.0447)	(0.0130)	(0.0131)	(0.00680)
Software (specific)	0.258***	0.247***	0.0812***	0.0595***	0.0302***
	(0.0549)	(0.0520)	(0.0119)	(0.00873)	(0.00510)
Computer (general)	-0.137***	-0.130***	-0.0848***	-0.0509***	-0.0300***
	(0.0321)	(0.0319)	(0.0109)	(0.00840)	(0.00573)
Cognitive	0.105***	0.105***	0.0314***	0.0341***	0.0157***
	(0.0244)	(0.0232)	(0.00838)	(0.00449)	(0.00346)
Social	0.0119	0.00883	0.00893*	0.0210***	0.00708***
	(0.0237)	(0.0213)	(0.00487)	(0.00341)	(0.00255)
Character	-0.147***	-0.148***	-0.0635***	-0.0360***	-0.0197***
	(0.0179)	(0.0172)	(0.00872)	(0.00465)	(0.00333)
Writing	0.0552	0.0512	0.0196**	0.00776	0.00463
	(0.0351)	(0.0344)	(0.00973)	(0.00489)	(0.00480)
Customer Service	-0.0226	-0.0144	-0.0170*	-0.0157***	-0.0120***
	(0.0597)	(0.0590)	(0.00908)	(0.00522)	(0.00366)
Project Management	0.290***	0.283***	0.132***	0.109***	0.0636***
	(0.0271)	(0.0272)	(0.0149)	(0.0114)	(0.00716)
People Management	0.148***	0.147***	0.0789***	0.0813***	0.0488***
	(0.0257)	(0.0238)	(0.00728)	(0.00464)	(0.00376)
Financial	0.173***	0.168***	0.0973***	0.0914***	0.0460***
	(0.0353)	(0.0344)	(0.00929)	(0.00739)	(0.00497)
Observations	12,304,519	12,304,518	12,247,697	9,923,378	6,424,944
R-squared	0.119	0.144	0.507	0.701	0.757
Year-month FE	✓	✓	✓	✓	✓
MSA FE		✓			
MSA× SOC FE			✓	✓	✓
Industry FE			✓		
Firm FE				✓	✓
Job Title FE					✓

Standard errors in parentheses clustered by MSA, SOC, and 3-digit NAICS
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Regressions of Log Wage on AI and Other Skills: By top 2-digit SOC occupations ranked by AI share of vacancies.
Estimation is for the period 2016-2019, and excludes internships. Standard errors are clustered by MSA and 3-digit NAICS industry. Columns are labeled using the following occupation names and abbreviations: Computer & Math - Computer and Mathematical (SOC 15), Architecture and Engineering (SOC 17), Science - Life, Physical, and Social Science (SOC 19), Management (SOC 11), Legal (SOC 23), Business & Financial - Business and Financial Operations (SOC 13).
Data source: Burning Glass Technologies

	Dependent Variable: Log Wage					
	Computer & Math (1)	Architecture & Engineering (2)	Science (3)	Management (4)	Legal (5)	Business & Financial (6)
AI	0.0878***	0.0472***	0.0746***	0.102***	-0.0399	0.0732***
	(0.00695)	(0.0158)	(0.0227)	(0.0159)	(0.0536)	(0.0103)
Software (specific)	0.140***	0.0341***	0.0169	0.0345***	0.00135	0.0306***
	(0.0129)	(0.00991)	(0.0118)	(0.00662)	(0.0106)	(0.00568)
Computer (general)	-0.0994***	-0.0267***	-0.0826***	-0.0856***	-0.0659***	-0.0696***
	(0.00465)	(0.00536)	(0.0157)	(0.0112)	(0.0125)	(0.00531)
Cognitive	0.0206**	0.0318***	0.0251***	0.0506***	0.0394**	0.0419***
	(0.00992)	(0.00608)	(0.00859)	(0.00661)	(0.0169)	(0.00607)
Social	0.0323***	0.0262***	0.0335***	0.0414***	0.0235***	0.0325***
	(0.00613)	(0.00382)	(0.00576)	(0.00404)	(0.00838)	(0.00404)
Observations	544,130	191,761	109,140	954,759	62,341	534,600
R-squared	0.613	0.731	0.738	0.628	0.757	0.634
Other Skills controls	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
MSA× SOC FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses clustered by MSA and 3-digit NAICS
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Regressions of Log Wage on AI and Other Skills: By top 2-digit NAICS Industries ranked by AI share of vacancies. Estimation is for the period 2016-2019, and excludes internships. Standard errors are clustered by MSA and 6-digit SOC occupations. Columns are labeled using the following industry names and abbreviations: Information (NAICS 51), Professional Services - Professional, Scientific, and Technical Services (NAICS 54), Finance & Insurance - Finance and Insurance (NAICS 52), Administrative & Support - Administrative and Support Services (NAICS 56), Agriculture - Agriculture, Forestry, Fishing and Hunting (NAICS 11), Manufacturing (NAICS 31-33).
Data source: Burning Glass Technologies

	Dependent Variable: Log Wage					
	Information	Professional Services	Finance & Insurance	Admin & Support	Agriculture	Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.108***	0.0816***	0.104***	0.177***	-0.0143	0.0896***
	(0.0280)	(0.0101)	(0.0101)	(0.0193)	(0.0290)	(0.0202)
Software (specific)	0.113***	0.0793***	0.0570***	0.0433***	0.0258**	0.0662***
	(0.0131)	(0.00791)	(0.0120)	(0.0127)	(0.0123)	(0.00807)
Computer (general)	-0.0819***	-0.0817***	-0.0782***	-0.0224**	-0.0306	-0.0326***
	(0.00768)	(0.00484)	(0.00646)	(0.0111)	(0.0193)	(0.00701)
Cognitive	0.0256**	0.0192***	0.0154**	0.0181	0.0163	0.0289***
	(0.00991)	(0.00469)	(0.00741)	(0.0112)	(0.0114)	(0.00528)
Social	0.0139	0.0279***	-0.00139	0.0212***	0.0414***	0.0264***
	(0.0107)	(0.00295)	(0.00914)	(0.00274)	(0.00990)	(0.00444)
Observations	240,022	829,057	571,423	675,318	21,539	730,758
R-squared	0.791	0.716	0.714	0.762	0.871	0.736
Other Skills controls	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
MSA× SOC FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses clustered by MSA and SOC
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Regressions of Log Wage of Non-AI Vacancies on Firm-Level AI Share of Vacancies.
Estimation is for the period 2016-2019, and excludes internships. Standard errors are clustered by MSA, 6-digit SOC occupation, and 3-digit NAICS industry.
Data source: Burning Glass Technologies

	Dependent Variable: Log Wage				
	(1)	(2)	(3)	(4)	(5)
Firm-Level AI Vacancy Share	3.138***	2.873***	1.235***	0.319**	0.169
	(0.395)	(0.357)	(0.123)	(0.133)	(0.110)
Software (specific)	0.241***	0.232***	0.0785***	0.0592***	0.0300***
	(0.0498)	(0.0477)	(0.0115)	(0.00869)	(0.00507)
Computer (general)	-0.134***	-0.128***	-0.0840***	-0.0508***	-0.0300***
	(0.0320)	(0.0318)	(0.0108)	(0.00844)	(0.00575)
Cognitive	0.100***	0.100***	0.0306***	0.0341***	0.0157***
	(0.0241)	(0.0230)	(0.00834)	(0.00450)	(0.00347)
Social	0.00880	0.00628	0.00833*	0.0210***	0.00713***
	(0.0234)	(0.0212)	(0.00481)	(0.00343)	(0.00256)
Character	-0.146***	-0.147***	-0.0630***	-0.0360***	-0.0198***
	(0.0180)	(0.0173)	(0.00863)	(0.00465)	(0.00335)
Writing	0.0569	0.0528	0.0200**	0.00801	0.00472
	(0.0347)	(0.0340)	(0.00965)	(0.00487)	(0.00482)
Customer Service	-0.0213	-0.0133	-0.0169*	-0.0157***	-0.0119***
	(0.0599)	(0.0591)	(0.00916)	(0.00523)	(0.00366)
Project Management	0.284***	0.278***	0.131***	0.109***	0.0640***
	(0.0270)	(0.0270)	(0.0147)	(0.0113)	(0.00714)
People Management	0.150***	0.148***	0.0789***	0.0813***	0.0489***
	(0.0261)	(0.0240)	(0.00731)	(0.00462)	(0.00376)
Financial	0.173***	0.169***	0.0977***	0.0917***	0.0460***
	(0.0351)	(0.0343)	(0.00933)	(0.00737)	(0.00497)
Observations	12,268,857	12,268,856	12,212,048	9,892,498	6,409,438
R-squared	0.121	0.145	0.506	0.700	0.757
Year-month FE	✓	✓	✓	✓	✓
MSA FE		✓			
MSA× SOC FE			✓	✓	✓
Industry FE			✓		
Firm FE				✓	✓
Job Title FE					✓

Standard errors in parentheses clustered by MSA, SOC, and 3-digit NAICS
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Regressions of Log Median Wage in 6-digit SOC-MSA market on Market-Level AI Share of Vacancies.
Estimation is for the period 2016-2017, and excludes internships. Dependent variable is log median hourly salary for 6-digit occupation-MSA market in the Occupational Employment Statistics (OES) provided by the Bureau of Labour Statistics. Education and work experience from the BGT data and the percentages of vacancies in each 2-digit NAICS industry within MSA-SOC market are included in all regressions. Columns 1 and 2 present regression results for the sample of all occupations, sample in columns 3 and 4 only includes professional occupations (SOC 11-29). Regressions are weighted by the total number of vacancies in the SOC-MSA market in columns 1 and 2 and the number of vacancies in professional occupations in the MSA-SOC market in columns 3 and 4. Standard errors are clustered by MSA and 6-digit SOC.
Data source: OES and Burning Glass Technologies

	Dependent Variable: Log Median Wage			
	All occupations		Professional occupations	
	(1)	(2)	(3)	(4)
Market-level AI share	0.549***	0.269**	0.443***	0.0350
	(0.191)	(0.122)	(0.161)	(0.196)
Software (specific)	0.237***	0.0575***	0.235***	0.0369
	(0.0843)	(0.0214)	(0.0849)	(0.0231)
Computer (general)	-0.143**	-0.0216	-0.189*	-0.0174
	(0.0708)	(0.0162)	(0.104)	(0.0238)
Cognitive	0.0837**	0.0121	0.00308	0.00784
	(0.0365)	(0.0109)	(0.0409)	(0.0218)
Social	0.0544	0.00582	-0.0153	-0.000701
	(0.0342)	(0.00994)	(0.0497)	(0.0156)
Character	-0.140***	-0.0216	-0.164***	-0.0300
	(0.0361)	(0.0170)	(0.0497)	(0.0211)
Writing	0.0424	-0.00195	-0.0325	-0.0277
	(0.0515)	(0.0210)	(0.0543)	(0.0247)
Customer Service	-0.0945**	-0.0376*	-0.0973	-0.0967**
	(0.0480)	(0.0225)	(0.0725)	(0.0393)
Project Management	-0.0727	0.0185	-0.00840	0.0400
	(0.0786)	(0.0521)	(0.0716)	(0.0465)
People Management	0.00886	-0.00813	0.0171	-0.0106
	(0.0645)	(0.0181)	(0.0780)	(0.0229)
Financial	0.126***	0.0369	0.102**	0.0157
	(0.0451)	(0.0244)	(0.0488)	(0.0274)
Observations	185,939	185,928	77,261	77,259
R-squared	0.904	0.957	0.786	0.902
Industry shares	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
MSA characteristics	✓		✓	
4-digit SOC FE	✓		✓	
MSA FE		✓		✓
6-digit SOC FE		✓		✓

Standard errors in parentheses clustered by MSA and SOC
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

A Appendix

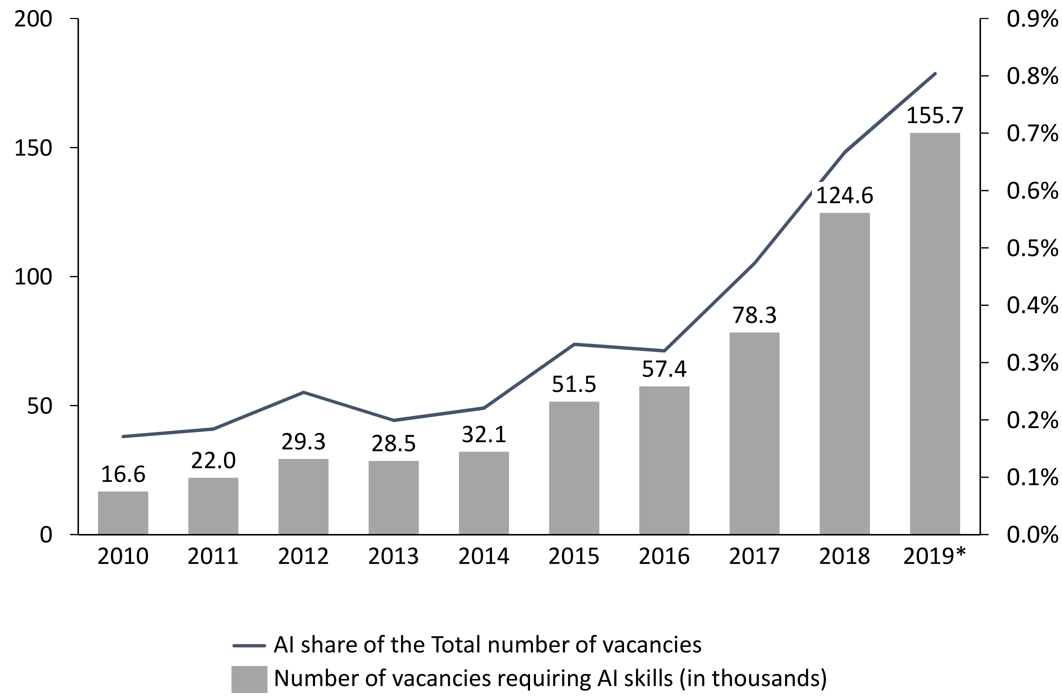


Figure A1. AI share of total hiring over time for employers that were present in the data each year of 2010-2019. The figure shows the number of vacancies requiring AI skills over time (bars) and the ratio of the number of vacancies requiring AI skills to the total number of vacancies (line), AI share. The data includes only firms that were present in BGT data each year of 2010-2019. The total number of vacancies requiring AI in 2019 is a projection based on the annualized number of vacancies posted in January-July, 2019.

Table A1. List of skills in the Burning Glass Technologies job vacancies dataset used to identify vacancies requiring AI skills.

N	**Skill**	**N**	**Skill**
1	AI ChatBot	31	Machine Translation (MT)
2	AI KIBIT	32	Machine Vision
3	ANTLR	33	Madlib
4	Apertium	34	Mahout
5	Artificial Intelligence	35	Microsoft Cognitive Toolkit
6	Automatic Speech Recognition (ASR)	36	MLPACK (C++ library)
7	Caffe Deep Learning Framework	37	Mlpy
8	Chatbot	38	Modular Audio Recognition Framework (MARF)
9	Computational Linguistics	39	MoSes
10	Computer Vision	40	MXNet
11	Decision Trees	41	Natural Language Processing
12	Deep Learning	42	Natural Language Toolkit (NLTK)
13	Deeplearning4j	43	ND4J (software)
14	Distinguo	44	Nearest Neighbor Algorithm
15	Google Cloud Machine Learning Platform	45	Neural Networks
16	Gradient boosting	46	Object Recognition
17	H2O (software)	47	Object Tracking
18	IBM Watson	48	OpenCV
19	Image Processing	49	OpenNLP
20	Image Recognition	50	Pattern Recognition
21	IPSoft Amelia	51	Pybrain
22	Ithink	52	Random Forests
23	Keras	53	Recommender Systems
24	Latent Dirichlet Allocation	54	Semantic Driven Subtractive Clustering Method (SDSCM)
25	Latent Semantic Analysis	55	Semi-Supervised Learning
26	Lexalytics	56	Sentiment Analysis / Opinion Mining
27	Lexical Acquisition	57	Sentiment Classification
28	Lexical Semantics	58	Speech Recognition
29	Libsvm	59	Supervised Learning (Machine Learning)
30	Machine Learning	60	Support Vector Machines (SVM)

Continued on next page

Table A1 – *Continued from previous page*

N	Skill	N	Skill
61	TensorFlow	67	Virtual Agents
62	Text Mining	68	Vowpal
63	Text to Speech (TTS)	69	Wabbit
64	Tokenization	70	Word2Vec
65	Torch (Machine Learning)	71	Xgboost
66	Unsupervised Learning		

Table A2. Regressions of Log Wage of Non-AI Vacancies on Firm-Level AI Share of Vacancies: By top 2-digit SOC occupations ranked by AI share of vacancies.

Estimation is for the period 2016-2019, and excludes internships. Standard errors are clustered by MSA and 3-digit NAICS industry. Columns are labeled using the following occupation names and abbreviations: Computer & Math - Computer and Mathematical (SOC 15), Architecture and Engineering (SOC 17), Science - Life, Physical, and Social Science (SOC 19), Management (SOC 11), Legal (SOC 23), Business & Financial - Business and Financial Operations (SOC 13).

Data source: Burning Glass Technologies

	Dependent Variable: Log Wage					
	Computer & Math (1)	Architecture & Engineering (2)	Science (3)	Management (4)	Legal (5)	Business & Financial (6)
Firm-Level AI Vacancy Share	0.196**	-0.00773	0.318	0.187*	1.081	0.356**
	(0.0821)	(0.129)	(0.323)	(0.0947)	(1.053)	(0.136)
Software (specific)	0.141***	0.0341***	0.0173	0.0345***	0.00162	0.0305***
	(0.0130)	(0.00991)	(0.0120)	(0.00664)	(0.0105)	(0.00560)
Computer (general)	-0.101***	-0.0267***	-0.0820***	-0.0858***	-0.0659***	-0.0696***
	(0.00471)	(0.00534)	(0.0157)	(0.0112)	(0.0124)	(0.00531)
Cognitive	0.0217**	0.0319***	0.0250***	0.0505***	0.0396**	0.0418***
	(0.0101)	(0.00604)	(0.00852)	(0.00657)	(0.0169)	(0.00611)
Social	0.0329***	0.0264***	0.0328***	0.0415***	0.0231***	0.0328***
	(0.00628)	(0.00373)	(0.00596)	(0.00407)	(0.00839)	(0.00398)
Observations	527,291	190,566	108,382	951,049	62,286	532,732
R-squared	0.610	0.731	0.739	0.627	0.757	0.634
Other Skills controls	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
MSA$\times$ SOC FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses clustered by MSA and 3-digit NAICS

*** p<0.01, ** p<0.05, * p<0.1

Table A3. Regressions of Log Wage of Non-AI Vacancies on Firm-Level AI Share of Vacancies: By top 2-digit NAICS Industries ranked by AI share of vacancies.

Estimation is for the period 2016-2019, and excludes internships. Standard errors are clustered by MSA and 6-digit SOC occupations. Columns are labeled using the following industry names and abbreviations: Information (NAICS 51), Professional Services - Professional, Scientific, and Technical Services (NAICS 54), Finance & Insurance - Finance and Insurance (NAICS 52), Administrative & Support - Administrative and Support Services (NAICS 56), Agriculture - Agriculture, Forestry, Fishing and Hunting (NAICS 11), Manufacturing (NAICS 31-33).

Data source: Burning Glass Technologies

	Dependent Variable: Log Wage					
	Information	Professional Services	Finance & Insurance	Admin & Support	Agriculture	Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
Firm-Level AI Vacancy Share	-0.0161	0.169***	0.162	0.323**	-0.0840	0.00361
	(0.405)	(0.0464)	(0.121)	(0.159)	(0.277)	(0.149)
Software (specific)	0.113***	0.0793***	0.0567***	0.0429***	0.0249**	0.0658***
	(0.0130)	(0.00791)	(0.0121)	(0.0127)	(0.0125)	(0.00808)
Computer (general)	-0.0824***	-0.0823***	-0.0780***	-0.0222**	-0.0300	-0.0324***
	(0.00777)	(0.00488)	(0.00645)	(0.0111)	(0.0192)	(0.00702)
Cognitive	0.0260***	0.0194***	0.0153**	0.0182	0.0171	0.0289***
	(0.0100)	(0.00466)	(0.00745)	(0.0112)	(0.0118)	(0.00529)
Social	0.0135	0.0284***	-0.00141	0.0213***	0.0406***	0.0265***
	(0.0108)	(0.00297)	(0.00920)	(0.00273)	(0.00977)	(0.00446)
Observations	237,674	817,165	567,675	674,399	21,400	727,869
R-squared	0.789	0.714	0.714	0.761	0.870	0.735
Other Skills controls	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
MSA$\times$ SOC FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses clustered by MSA and SOC
*** p<0.01, ** p<0.05, * p<0.1

Table A4. Regressions of Log Median Wage in 6-digit SOC-MSA market on Market-Level AI Share of Vacancies (Unweighted). Estimation is for the period 2016-2017, and excludes internships. Dependent variable is log median hourly salary for 6-digit occupation-MSA market in the Occupational Employment Statistics (OES) provided by the Bureau of Labour Statistics. Education and work experience from the BGT data and the percentages of vacancies in each 2-digit NAICS industry within MSA-SOC market are included in all regressions. Columns 1 and 2 present regression results for the sample of all occupations, sample in columns 3 and 4 only includes professional occupations (SOC 11-29). All regressions are unweighted. Standard errors are clustered by MSA and 6-digit SOC.
Data source: OES and Burning Glass Technologies

	Dependent Variable: Log Median Wage			
	All occupations		Professional occupations	
	(1)	(2)	(3)	(4)
Market-level AI share	0.523***	0.0913***	0.561***	0.0856***
	(0.0876)	(0.0275)	(0.0981)	(0.0309)
Software (specific)	0.122***	0.0144***	0.147***	0.0138**
	(0.0262)	(0.00415)	(0.0360)	(0.00607)
Computer (general)	-0.0270	-0.00726**	-0.0724**	-0.0111**
	(0.0193)	(0.00319)	(0.0297)	(0.00487)
Cognitive	0.0499***	0.00761**	0.0344	0.00941*
	(0.0172)	(0.00309)	(0.0278)	(0.00519)
Social	0.00188	0.00239	0.00439	0.000739
	(0.0120)	(0.00301)	(0.0195)	(0.00497)
Character	-0.0529***	-0.00449	-0.0721***	-0.0113**
	(0.0130)	(0.00303)	(0.0198)	(0.00551)
Writing	0.0585***	0.00212	0.0188	-0.00209
	(0.0219)	(0.00511)	(0.0267)	(0.00682)
Customer Service	-0.0532***	0.000234	-0.0712**	-0.00711
	(0.0196)	(0.00293)	(0.0309)	(0.00487)
Project Management	0.0968**	0.0128**	0.117***	0.0163**
	(0.0383)	(0.00594)	(0.0409)	(0.00647)
People Management	-0.0355	0.00430	-0.0303	-0.00290
	(0.0242)	(0.00403)	(0.0334)	(0.00536)
Financial	0.0553**	0.00340	0.0509**	0.00182
	(0.0218)	(0.00412)	(0.0245)	(0.00648)
Observations	185,939	185,928	77,261	77,259
R-squared	0.764	0.904	0.623	0.851
Industry shares	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
MSA characteristics	✓		✓	
4-digit SOC FE	✓		✓	
MSA FE		✓		✓
6-digit SOC FE		✓		✓

Standard errors in parentheses clustered by MSA and SOC
*** p<0.01, ** p<0.05, * p<0.1