AI Adoption and the Demand for Managerial Expertise*

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ABSTRACT

This paper investigates how AI adoption influences the demand for managers and their required skills. Using a skills-based measure of AI adoption derived from Lightcast job postings data, we show that when firms intensify their AI adoption they experience a significant increase in the number and share of managerial vacancies, indicating that AI implementation drives a greater demand for managerial roles. Furthermore, AI adoption shifts the skill requirements for managers, increasing the demand for cognitive and interpersonal skills such as collaboration, creativity, stakeholder management, and data analysis, while reducing the need for routine administrative skills like scheduling and budgeting. These findings suggest that AI reshapes organizations by increasing the importance of managerial expertise and by changing managerial roles and responsibilities within firms.

Keywords: artificial intelligence; managers; skills; technology adoption

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1. Introduction

The integration of advanced technologies has long been recognized as a driver of organizational innovation and transformation. In particular, Information and Communication Technologies (ICT) have been instrumental in reshaping firm structures (e.g., Bresnahan, Brynjolfsson and Hitt, 2002, Brynjolfsson, Hitt and Yang, 2002), enabling decentralization, improving coordination, and enhancing managerial effectiveness. ICT, such as Enterprise Resource Planning (ERP) systems, have helped broaden managerial spans of control, reduce decision-making bottlenecks, and improve productivity by automating key processes (Bloom et al., 2014). However, as firms continue to evolve, artificial intelligence (AI) is emerging as a new technological disruption that may fundamentally reshape managerial structures.

While ICTs have been pivotal in automating routine tasks and facilitating communication, AI presents a different challenge due to its unique capabilities in knowledge work and decision-making (Ide and Talamas, 2023, Bloom et al., 2014, Brynjolfsson and Mitchell, 2017). AI, unlike ICT, is not merely a tool for faster processing of information or smoother communication; it is a form of automation that can mimic human cognition, making decisions, learning from data, and solving complex problems that previously required human judgment. This positions AI as a transformative force, potentially significantly more transformative than previous technological innovations. The distinction between AI and ICT is crucial because while ICT largely supported decentralization by empowering lower levels of the hierarchy with better information (Bloom et al., 2014), AI might influence management structures in ways we do not fully understand yet, potentially increasing control at the top of the organization (Dell'Acqua et al., 2023, Ide and Talamas, 2023).

Despite the growing implementation of AI technologies across industries, the effects of AI on firm management and hierarchies remain underexplored. In this paper, we hypothesize that AI is distinct from traditional ICT in its capacity to fundamentally alter management

structures. Unlike ICT, which has been shown to decentralize decision-making, AI could both centralize and intensify management by enabling a small group of highly skilled managers to oversee larger teams with the help of advanced predictive technologies (Ide and Talamas, 2023). We propose that the adoption of AI leads to an increase in managerial responsibilities, as AI systems require ongoing oversight, tuning, and integration with existing business processes, rather than simply automating tasks.

Our hypothesis is grounded in the emerging literature on AI's impact on firm structures. The introduction of AI systems into organizations presents a new layer of complexity for managers, adding to their oversight and coordination responsibilities. As highlighted by Dell'Acqua et al. (2023), AI systems are often opaque, interactive, and capable of instantaneous decision-making. This requires managers to adapt their strategies for supervising both human and AI workers, integrating these systems into workflows while ensuring that they complement human efforts. Ide and Talamas (2023) further emphasize that AI's ability to mimic human behavior across different roles introduces the need for careful management of this hybrid workforce. These dynamics suggest that AI will not diminish the role of managers but rather expand it, as they will need to oversee increasingly complex systems where human and AI workers interact. The sheer intricacy of coordinating between human teams and algorithmic systems can create a higher demand for managerial oversight, as managers are responsible for interpreting AI outputs and ensuring seamless collaboration across the organization.

Additionally, managers will play a critical role in interpreting AI-generated insights, ensuring that these insights align with organizational goals, and making judgment calls that require human intuition and ethical consideration. Bloom et al. (2014) suggest that while information technology can empower workers and decentralize decision-making, the increased flow of information that AI introduces can overwhelm workers unless properly managed. Managers will need to ensure that AI-driven processes do not create information

overload and that decision-making remains effective. This indicates that far from reducing the need for managers, AI may require more human oversight to ensure that AI outputs are actionable and ethically sound.

Finally, some evidence suggests that AI could concentrate decision-making power, centralizing authority and altering traditional managerial roles (Gulati, Marchetti and Puranam, 2023, Ide and Talamas, 2023). At the same time, it could reduce the need for middle managers by automating tasks previously requiring human supervision (Dell'Acqua et al., 2023). Therefore, understanding how AI affects managerial intensity—defined as the proportion of managers to total employees—is critical to assessing the broader organizational impact (Gulati, Marchetti and Puranam, 2023).

As AI continues to reshape the workforce and management roles, the skill sets required of managers are also likely to evolve. The increasing complexity of overseeing both AI systems and human workers demands that managers develop strong combination of analytical and interpersonal skills. While AI is handling a growing share of routine activity, the human workforce will increasingly handle exceptions and unexpected situations, requiring increasing creativity and problem-solving skills from managers in particular. Thus, managers can be expected to excel in communication and creative problem-solving to ensure that AI complements rather than disrupts human tasks. Meanwhile, traditional administrative managerial tasks may become less central, as AI systems take on routine responsibilities. This shift would reflect a broader change in the nature of management in AI-augmented organizations, where soft skills should be increasingly valued alongside technical expertise.

We follow prior literature (e.g., Acemoglu et al., 2022, Alekseeva et al., 2021, Babina et al., 2024) and leverage detailed job postings data from Lightcast (formerly Burning Glass Technologies) to estimate AI adoption at the firm level based on the demand for AI-related skills. The online job vacancy data collected by Lightcast contains nearly the universe of online job postings in the United States (Acemoglu et al., 2022) and is able to capture in

detail the demand for AI skills in the labor market. To measure AI adoption, we develop a skill-based approach, identifying AI-related job postings as containing skills highly associated with artificial intelligence, machine learning, natural language processing, and computer vision. We then calculate the ratio of AI-related vacancies to the total number of vacancies for each firm, providing a proxy for AI adoption over time.

Our empirical analyses focus on understanding how AI adoption influences the demand for managerial roles and the specific skills required of managers. To achieve this, we employ firm-level panel data for a large universe of listed firms in Compustat that we were able to carefully match with the Lightcast vacancies data for the 2010-2022 period. We use two methodological approaches. First, we use regressions with fixed effects, controlling for various financial and operational characteristics, including firm size, employment, and IT capabilities. Second, recognizing the strong concerns for endogenitiy, we employ a Bartik-style instrumental variable approach (IV) (Bartik, 1991) suitable for long-run studies. This instrument captures firms' exogenous exposure to AI adoption based on the AI intensity of nearby firms, helping us address any reverse causality or omitted variable bias. By applying these two methods and a set of robustness test, we aim to provide careful insights into how AI is reshaping managerial roles, responsibilities, and skill sets within firms.

Our results show an economically significant increase in the demand for managerial roles as firms adopt AI technologies. We find that firms with higher levels of AI adoption post more managerial vacancies, both in absolute terms and as a share of their total vacancies. A one percentage point increase of our AI adoption measure translates into an increase between 2.5% and 7.5% of total management vacancies and an increase between 0.4% and 1.4% in the share of managers. This indicates that rather than reducing the need for managers, AI-driven transformations intensify managerial demands. The effect is stronger for the later period of the sample indicating that as AI systems mature, firms increasingly seek managers who can navigate AI-driven environments.

Next, we explore how AI adoption impacts the skill requirements for managers. Our hypothesis posits that managerial responsibilities are likely to expand due to the complex oversight and integration required for AI systems; if so, we should observe changes in the skill set required for managers. We find a growing demand for cognitive and interpersonal skills, such as teamwork, collaboration, creativity, and data analysis, while the need for routine administrative skills, such as scheduling and budgeting, declines. This shift suggests that AI adoption leads managers to focus more on strategic, problem-solving tasks and less on routine activities that can be automated. Finally, our analysis of posted wage data shows that overall managerial salaries tend to rise with AI adoption, though not disproportionately compared to other roles, indicating a general uplift in the value of labor across the organization when it increases AI adoption. Together, these findings highlight the transformative impact of AI on both the structure of managerial work and the competencies required for managerial success.

2. Estimating AI Adoption through skills

2.1. The Measure of AI Adoption

Estimating a firm-level AI adoption has been a big challenge for researchers. Indeed, given the lack of large-scale datasets on the AI technology adoption, it is impossible to know weather and to what extent firms are using AI. However, in order to proxy for AI adoption, we leverage the insight that AI technology, in contrast with some other technologies, requires highly-specialized human capital.[1] Thus, this paper uses a skilled-based definition of AI adoption using the data from job postings provided by Lightcast (former Burning Glass

[1]For instance, Tambe (2014) discusses the importance of highly skilled labor to extract value from big data technologies, and the number of IT workers as a measure of the firm's IT investments has been widely used in the literature (e.g., Tambe and Hitt, 2012, Tambe, Hitt and Brynjolfsson, 2012, Tambe et al., 2019). Following the insights from this literature, the demand for AI-related employees' skills may allow us to proxy for the level of AI technology adoption within firms. In this, we also follow research that used skilled-based measures of AI adoption at the firm level (Alekseeva et al., 2021, Acemoglu et al., 2022, Goldfarb, Taska and Teodoridis, 2023, Babina et al., 2024).

Technologies).

Lightcast is one of the leading providers of labor market data, and its vacancies database has been extensively used in the research on labor markets and technology adoption (e.g., Alekseeva et al., 2021, Goldfarb, Taska and Teodoridis, 2023, Babina et al., 2024, Gulati, Marchetti and Puranam, 2023). Our version of the Lightcast dataset contains details on almost 375 million vacancies in the United States posted between 2010 and 2022 and offers a great granularity of skill description and other details within each job posting. More specifically, the job postings data includes details such as name and industry of the employer, job title, location, and wage offered. It also provides details on the profile of the desired job candidates, including education, work experience, and, most importantly, a list of skills required from a potential employee. This level of detail provided in each individual job vacancy represents one of the main strengths of the Lightcast data, as it allows us to examine skill requirements in a specific job or occupation as well as to conduct a firm-level analysis of the demand for various skills. Lightcast uses an advanced algorithm to extract individual skills from vacancies and to classify them into standardized skills and skill clusters. The combination of these features make Lightcast one of the rare data sources that allows researchers to track the demand for AI skills and proxy for the adoption of the AI technology by firms.

In the core analysis, we use a data-driven approach to identifying AI-related vacancies. The intuition behind this approach is to estimate how much a job vacancy is associated with performing AI-related tasks by exploring the data rather than trying to predetermine which skills relate to AI ex-ante. More specifically, by evaluating how often a skill required in vacancies co-occurs with unambiguous AI skills, we can identify whether it is AI-related. If a vacancy contains more AI-related skills, it is therefore more likely to be AI-related itself. Such probabilistic approach is often used in other settings to estimate the association measures when no direct measures are available, but was first used to identify AI-related

vacancies in Babina et al. (2024).

Thus, we follow this approach and define whether a vacancy is AI-related following several steps. First, we find vacancies that have skills or job titles containing "Machine Learning", "Natural Language Processing", "Computer Vision", and "Artificial Intelligence", or their abbreviations. Second, for each skill present in the vacancies data, we estimate the proportion of times this skill appears in AI vacancies identified in the first step to the number of times the skill appears in all vacancies. This ratio represents the degree of AI-relatedness of a specific skill. Third, for each job posting, we calculate an average AI-relatedness across all the skills listed in the posting (excluding skills that appear in fewer than 20 vacancies in the data). Finally, we define the vacancy as AI-related if the average of its skills' AI-relatedness is above 10%.[2]

We calculate our main measure of AI adoption in firm i and time t as the ratio of AI-related job postings over the total number of the firm's job postings:

$$\text{AI Share}_{i,t} = \frac{\text{Number of AI-related Job Postings}_{i,t}}{\text{Total Number of Job Postings}_{i,t}}$$

Figure 1 shows the evolution of this measure of AI adoption over time. Panel A shows that the average share of jobs that require AI skills increased ten-fold in the 2010-2022 period, going from 0.1% to 1% of firms' vacancies. The share declined slightly between 2020 and 2021, but increased again between 2021 and 2022.

In our robustness tests, we also use a continuous measure of AI adoption (*Continuous AI Share*) that is equal to the average vacancy-level AI-relatedness defined in step three above, at the firm level. We also conduct robustness tests replacing the measure of *AI Share* estimated using the data-driven method described above with a measure of AI adoption using keywords to identify AI-related vacancies. The latter approach was employed in Alekseeva

[2]This threshold is rather arbitrary, but follows the research of Babina et al. (2024) who showed that it captures well the relevant AI skills.

et al. (2021) and relies on the list of pre-specified skills related to AI technology listed in Table A1. This list includes such core AI skills as "Machine Learning," "Natural Language Processing," and "Computer Vision," as well as more specific tools and frameworks like "TensorFlow," and "IBM Watson." Then a vacancy is defined as AI-related if it requires at least one of these pre-specified skills. While the bag-of-words method can be criticised, it is also fully transparent and likely to capture more of the AI jobs containing many non-AI-related skills driving the AI-relatedness score down, as might be the case in managerial jobs.

This keywords-based method is also in line with Goldfarb, Taska and Teodoridis (2023) who used a bag-of-words approach to measure the adoption of several general-purpose technologies. They argue that this approach allows to capture early technology diffusion because firms are likely to be specific about the needed technology skills in their job postings. Figure A1 shows that the measures of AI adoption based on the job AI-relatedness score and keywords have similar trends, with a keywords-based measure lying above our main measure of *AI Share*. This suggests that, overall, the two measures are consistent, with keywords-based measure capturing some additional AI-related vacancies. Therefore, *AI Share* based on job's AI-relatedness score can be considered a more conservative approach to measuring AI adoption.

In order to illustrate the evolution of the demand for AI skills in specific companies, Figures A2 and A3 show the trend of the demand for AI skills (Panel A) and the structure of the demand for AI skills across various detailed occupations (Panel B) at Procter & Gamble and Amgen included in our sample. It is clear that, in line with the general pattern, both companies started substantially increasing AI hiring in 2016. Both the number of AI vacancies and *AI Share* jump in 2016 and then continues growing (with some fluctuations). It is interesting to observe for which roles companies search AI specialists. Procter & Gamble Co. primarily searched for AI skills in Computer and Mathematical Occupations, but since

2020 an increasing share of AI job postings is in Engineering. This suggests a potential switch from such tasks as data analysis typical in Computer and Mathematical jobs to engineering AI solutions within the firm. The case of Amgen also shows the largest share of AI postings in Computer occupations, while also demanding managers, life scientists, as well as engineers with AI knowledge. Thus, from this structure of AI hiring, we can observe that AI adoption is not limited to one specific area of the organization and that AI can be applied across various processes and functions.

For our analysis, we also calculate *Managers Share* and various *Managerial Skill Shares*. For the *Managers Share* calculation, we divide the number of vacancies in management occupations (2-digit SOC code 11) within the firm to the total number of the firm's vacancies. Respectively, to estimate how much a specific skill is demanded in managerial jobs, we divide the number of firm's managerial vacancies requiring the skill to the total number of managerial vacancies of this firm. In our analysis, we focus on top-100 skills demanded in managerial vacancies, where we identify these top skills by ranking the frequency with which they occur on the overall Lightcast data. Lightcast vacancies contain more than 16 thousand unique skills. Therefore, it would be computationally challenging to analyze all of them. Thus, we focus on the most prevalent managerial skills. Finally, we calculate the intensity of Software skills in the company to use as a control variable by dividing the number of vacancies requiring Software skills to the total number of vacancies in the company.

The demand for managers in firm i and time t is calculated as follows:

$$\text{Managers Share}_{i,t} = \frac{\text{Number of Job Postings in Management Occupation}_{i,t}}{\text{Total Number of Job Postings}_{i,t}}$$

At the same time, the demand for the specific skills within managerial vacancies in firm

i and time t is calculated using the following ratio:

$$\text{Managerial Skill } j \text{ Share}_{i,t} = \frac{\text{Number of Job Postings in Management Requiring Skill } j_{i,t}}{\text{Total Number of Job Postings in Management}_{i,t}}$$

In contrast with a clear rising trend for *AI Share*, the share of managerial vacancies declined from around 21% in 2010 to around 19% in 2022, as can be seen in Panel B of Figure 1. In fact, the lowest share of managerial vacancies is observed in 2017, with 18.5% of vacancies demanding managers. There was a rebound in the demand for managers up to 19.5% in 2020, with a following decline in the last two years of the sample. The next section examines more closely whether the trends for *AI Share* and *Managers Share* are related.

We acknowledge several limitations of using the job postings data to proxy actual employment. Clearly, the posted position is not always filled and the description of the job profile in the vacancy may not match the profile of the actual employee hired for this position. However, a recent paper by Babina et al. (2024) specifically explores the similarity between the demand for AI-skilled employees in Lightcast vacancies and the actual employment of workers with AI skills based on the resume data from Cognism. The authors find that the two measures of the AI hiring intensity - based on vacancies and resumes - have a strong correlation and generate similar results in the analysis of the AI impact on firm performance. Additional analysis of the quality of the job postings data was conducted by Carnevale, Jayasundera and Repnikov (2014) and Hershbein and Kahn (2018). The studies showed that Lightcast ("Burning Glass" in these papers) online job postings correlate strongly with the job openings data in JOLTS and that the aggregate and industry trends of the number of vacancies in the Lightcast data are consistent with other sources of job vacancies data, such as CPS, OES and JOLTS. Overall, given the detailed information contained in job descriptions, the timely nature of job postings, and consistent patterns in comparison with broader job data, Lightcast job postings data provides a unique source of information

which allows us to trace the demand for AI talent across firms and in various occupations within firms.

2.2. Sample

Our Lightcast data consists of all job vacancies in the US, excluding internships, from January 2010 until December 2022, which encompasses a total of approximately 370 million vacancies. After dropping vacancies that do not have employer name, we still have the sample of around 260 million vacancies that we match to Compustat dataset. We focus on the Compustat-matched sample to be able to control for company financial characteristics and classify companies reliably into industry sectors. It also allows us to avoid including non-commercial organizations (e.g., government agencies) in the sample. We conduct a thorough match between Lightcast vacancies data and Compustat using several matching approaches. First, the databases were matched based on the company names in both databases, with an extensive manual check of imprecise matches. We supplemented this link with company matching based on an algorithm using Bing Web Search API described in Autor et al. (2020). This algorithm matches firms not only on their name, but also on whether search results with the use of their names return the same URLs among the top results. This method, therefore, well captures those cases when there was a company name change, when databases use abbreviations or short versions of company names. This matching procedure delivers 80 million vacancies matched with Compustat.

From the main analysis we exclude firms that produce AI or help implement AI solutions for other companies (2-digit NAICS equal 51 and 54). We drop observations with missing values for variables used as controls, and we drop companies which have fewer than 30 managerial vacancies or which appear in the sample only once. Even though we use the data over 2010-2022 to construct the descriptive graphs, we exclude 2010 from the regressions, as we use 2010 data in instrument calculation. The resulting sample used in the regressions

includes 2,322 unique companies, resulting 16,021 observations at the company-year level.[3]

Table 1 provides summary statistics for the AI adoption and managerial vacancies in the sample. It shows that, on average, 0.5% of companies' vacancies represent AI-related postings, as measured by *AI Share*. As we have seen in Figure A1, using a keywords-based measure suggests a slightly higher average AI adoption rate (0.7%). The table also shows that 19.1% of company vacancies represent managerial jobs.

The table additionally characterizes managerial vacancies in terms of the required skills. It highlights some of the most frequently demanded skills within managerial vacancies. Communication skills top the list, with nearly 50% of managerial vacancies demanding them, followed by Budgeting (29.7%), Planning (27.8%), and Teamwork / Collaboration (27.6%). It also highlights the prevalence of more technical skills like Project Management (22.3%) and Scheduling (18.4%). Thus, the table reflects the multifaceted nature of managerial jobs in organizations, with both soft skills and technical competencies highly demanded in managerial jobs. Descriptive statistics for the full list of top-100 required managerial skills in Appendix Table A2 includes both more and less popular managerial skills (e.g., Communication Skills (49.6%), Problem Solving (23.0%), Sales (16.4%)), as well as Risk Management (2.7%), Editing (1.7%), Bilingual (1.5%)).

Table 2 tracks the change in key vacancy characteristics and managerial skills between 2011, 2016, and 2022. The data shows a substantial increase in AI-related job postings. In contrast, it shows that the share of managerial vacancies has declined since the beginning of the observation period, consistent with the trend observed in Figure 1. Interestingly, the change in the demand for the top-10 managerial skills presented in the table is primarily positive (it is also overwhelmingly positive but not tabulated for the remaining top skills). Therefore, in the managerial vacancies, most of the top skills are increasing in demand.

[3]Table 1 shows Compustat-based financial and operational characteristics of the firms used in the regressions. All monetary variables are adjusted for inflation and ratios are winzorised at 1 and 99 percent levels. We also winsorize at 1 and 99 percent all ratios that are estimated based on the vacancy data.

Finally, Table 1 shows that approximately 0.3% of managerial jobs can be classified as AI-related. Panel B of Figure A1 shows that while the share of AI-related managerial vacancies is below the overall AI share, it has also grown steadily over the analyzed period, with the acceleration of growth around 2016. This indicates a rising demand for managers with AI skills.

3. Empirical Methodology

3.1. AI Adoption and the Demand for Managers

To study the effect of AI adoption by firms on their demand for managers, we estimate the following regression specification:

$$\text{Managers Share}_{i,t} = \beta \text{AI Share}_{i,t} + \gamma X_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}. \tag{1}$$

Managers Share$_{it}$ is the share of managerial vacancies in a firm, *AI Share*$_{it}$ is the main variable of interest estimated as described in section 2.1. and multiplied by a 100 to aid the interpretation of the results (each coefficient can be directly interpreted as a change in the dependent variable in the result of a percentage-point change in *AI Share*), X_{it} is a vector of controls for company financial and operational characteristics, and δ_i and θ_t are firm and year fixed effects. Control variables include *Software Share* (the share of vacancies requesting specialised software skills), the natural logarithm of sales, the natural logarithm of employment, cash-to-assets ratio, R&D-to-sales ratio[4], and the natural logarithm of total firm's vacancies.

[4]We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data.

3.2. AI Adoption and the Demand for Managerial Skills

We analyze how the profile of managers changes when firms adopt AI technology using the following regression specification:

$$\text{Managerial Skill } j \text{ Share}_{i,t} = \beta_1 \text{AI Share}_{i,t} + \gamma X_{i,t} + \delta_i + +\theta_t + \varepsilon_{i,t}. \quad (2)$$

Managerial Skill Share$_{it}$ is the share of managerial vacancies requiring one of the top-100 managerial skills in a firm, *AI Share*$_{it}$ is the main variable of interest estimated as described in section 2.1. and multiplied by a 100, X_{it} is a vector of controls for company financial and operational characteristics as described above, and δ_i and θ_t are firm and year fixed effects.

3.3. Identification strategy for AI adoption

There are several endogeneity concerns related to the causal estimation of the effect of AI adoption on firm labor force structure and the demand for skills. First, there is likely to be an omitted variables problem. We use firm fixed effect regressions to control for time-invariant omitted firm characteristics and include several controls that might be related to changes in the firm organization. However, we cannot address the problem of omitting other important time-varying characteristics, such as within-firm processes transformation, change in the organizational structure, or changing management quality. Second, AI adoption and changes in firms' demand for managers and various managerial skills can simply occur simultaneously: the demand for AI skills and the demand for managers and some managerial skills can simply follow similar trends. Third, there might be a reverse causality: firms with high managerial intensity can try to hire more AI specialists to optimize their work. Finally, there might be a measurement error because *AI Share* can be an imperfect proxy for the level of AI adoption and it is likely to be a noisy measure, as firms can post more AI-related vacancies than needed and they might look for AI specialists via alternative ways (e.g., acquihires or

employee training).

We use a Bartik-style instrumental variable to deal with the endogeneity problems described above. In our application, the instrument's logic is to measure the firm's exogenous exposure to AI adoption, based on the AI adoption by companies surrounding the focal firm. Thus, if the firm is surrounded by other companies belonging to industries that adopt AI more intensively, the firm itself will be more likely to use AI to a larger extent.

This firm-level exposure to AI is predicted by the interaction of the local industry employment shares with the country-wide industry-specific AI adoption rates. More specifically, to estimate the instrument, we first calculate the shares of employment in 3-digit NAICS industries in commuting zones of the firm location in 2010 using information provided by the U.S. Census Bureau's Business Patterns survey. We keep this commuting zone-level employment structure constant to avoid bias stemming from industries adjusting employment shares in response to the investment opportunities. Then, we multiply these constant shares by the industry-specific economy-wide *AI Shares*. Therefore, the local exposure to AI of firm i (located in market m) in time t equals:

$$B_{i,m,t} = \sum_{s=1}^{S} w_{m,s,0} \text{AI Share}_{s,t}, \tag{3}$$

where $w_{s,m,0}$ is the pre-period (2010) share of industry s's employment in commuting zone m; $AI\ Share_{s,t}$ is *AI Share* in industry sector s and time t. We note that in Lightcast data firms might post vacancies in various locations, reflecting the locations of their establishments. Therefore, when we calculate the firm-level AI exposure measure, we estimate a weighted average the firm's establishment-level exposure to AI using the shares of firm's vacancies across establishments as weights. We use these weights as of 2010 to construct the IV for regressions using 2011-2022 and 2011-2015 sample periods, and we use 2015-based weights for the IV in 2016-2022 period analyses. This adjustment allows us to increase the sample of

firms in the 2016-2022 sample, as with 2015-based weights it is not limited only to companies that posted vacancies in 2010.

Goldsmith-Pinkham, Sorkin and Swift (2018) showed that the validity of the Bartik instrument rests on the exogeneity of shares used in the projection of the chosen average growth rates. Thus, constructing our Bartik-style IV based on the described approach, we assume that industries' employment shares do not correlate with the firm's demand for managers and managerial skills we analyse. Clearly, we also assume that the location of firm establishments across commuting zones is not correlated with the outcomes we analyse. Nevertheless, to control for possible confounding effects (e.g., investment opportunity shocks and firm growth), in all regressions, we control for a range of firm's financial and operational characteristics using data from Compustat. Additionally, in all regressions, we also include a proxy for the firm's IT capabilities (e.g., Tambe and Hitt, 2012, 2014), measured as the percentage of vacancies requiring specialized software skills, *Software Share*. When reporting the IV regression results, in all tables, we report the Kleibergen-Paap F-statistics.

4. Results

4.1. AI Adoption and the Demand for Managers

Table 3 presents regression results showing how AI adoption influences the demand for managers in the analyzed firms. Both OLS and instrumental variable models that follow specification 1 indicate a positive relationship: firms with higher AI adoption tend to post more managerial vacancies and require a larger share of managers. This first result suggests that, as AI is getting integrated into business operations, the demand for managers grows both in absolute terms and as a share of total labor demand. It is important to note that in all regressions we are controlling for the extent of IT expertise in the company using *Software Share*, as well as for firm size, cash availability, and R&D intensity, with the latter

three characteristics being the typical predictors of AI adoption by companies (Alekseeva et al., 2021, Babina et al., 2024).

The economic magnitude of the effect of AI adoption on the demand for managers is significant. The OLS results suggest that when the firm's *AI Share* increases by one percentage point, the number of posted managerial vacancies rises by 2.4% (column (1)) and the firm's *Managers Share* increases by 0.4 percentage points, or by around 2% relative to the unconditional mean (column (3)). However, the IV results suggest that this size of the effect estimated by OLS regressions might be biased downwards, as in both columns (2) and (4) the magnitude of the coefficient of *AI Share* is larger. Thus, IV regressions indicate that when *AI Share* of the firm increases by one percentage point, the number of managerial vacancies grows by 7.5% (column (2)) and *Managers Share* grows by 1.4 percentage points, or by around 7%.

Next, we divide the data into two sub-periods (2011-2015 and 2016-2022) to explore how the effect of AI adoption on the demand for managers varies with time. We use 2016 as a cut-off year between the two sub-periods as it is when the trend of AI adoption in the US economy substantially accelerated (see Figure 1) and therefore could influence the firm transformation differently. Table 4 shows that the effect of AI adoption on managerial demand statistically is stronger in the later sub-period, as the coefficients' standard errors are relatively smaller. However, we have to be careful comparing the coefficient magnitudes between these two sub-periods, since each period has different means and standard deviations of *AI Share* and *Managers Share*. While the variation in *Managers Share* is limited over time, average *AI Share* and its standard deviation change substantially between the sub-samples: standard deviation of *AI Share* is 0.4% in 2011-2015 and 1.6% in 2016-2022 (see Table 1). Therefore, interpreting results in terms of the change in *AI Share* by a standard deviation rather than by a percentage point might be more intuitive. Therefore, in terms of economic magnitude, the IV regressions suggest that one standard deviation increase in *AI Share* is related to

nearly 15% and 17% increase in the number of managerial vacancies in the earlier and later periods, respectively (column (2) of Panels A and B). Also, one standard deviation increase in *AI Share* is related to 1.8 and 3.7 percentage points increase in *Managers Share* (or 9% and 20% increase in unconditional means in the respective periods). Thus, the effect of AI adoption on the demand for managers intensified over time.

Overall, the results support a stronger impact of AI adoption on the number of managerial vacancies in the 2016-2022 period, suggesting that, as AI technologies mature, firms increasingly seek managers who can navigate AI-driven environments.

4.1.1. Heterogeneity

Table 5 explores AI's impact on the demand for managers across different industries. Manufacturing is the sector that experienced the largest increase in managerial vacancies in the result of AI adoption, in the absolute number and as a share of total vacancies. At the same time, Finance, Trade, and the remaining industries grouped under "Other" show less clear trends. Even though the IV regressions coefficients for Finance and Other are positive, their standard errors are large in the regressions studying the number of managerial vacancies and their share. Therefore, the data suggests that the impact of AI adoption on managerial demand varies significantly by sector.

In Table 6, we explore whether the AI adoption is complemented by the hiring of managers with AI skills and whether the firms try to hire AI managers with a higher intensity than other manager types. To run these regressions we adjust our independent variable *AI Share* to exclude any managerial positions that could be included in it, and we use the number and share of AI managers in the company as the dependent variable. First, we can observe that not every firm strives to hire managers with AI skills, as the sample becomes substantially smaller when we analyze the change in the number of vacancies for AI managers in columns (1) and (2). Even though the OLS specification in column (1) suggests a positive

correlation between the natural logarithm of the number of vacancies for AI managers and non-managerial AI vacancies, the IV regression delivers an insignificant coefficient. However, we also have to note that the F-statistics is significantly below 10 in this specification. Thus, we cannot confidently comment on the IV results in column (2). However, both OLS and IV regressions show a positive and statistically significant result in the regressions with *AI Managers Share* as the dependent variable (columns (3) and (4)). The magnitude of the coefficient in the IV regression (column (4)) suggests that with one percentage point increase in the share of non-managerial AI vacancies, *AI Managers Share* increases by 0.1 percentage points, which is equivalent to nearly 33% increase in the unconditional mean, which is equal to 0.3%.[5] Thus, the effect of AI adoption (when measured using only non-managerial vacancies) is related to a significantly stronger increase in AI managers positions. This is not surprising, considering still a relatively low number of such positions in our data: on average in our sample, a company has four AI managers, while the total number of managers is more than 500.

Finally, we also explore which types of managers experience an increase in demand when firms adopt AI. We leverage the detailed occupational classification available in the vacancies and categorize all managerial vacancies into subgroups based on the 3-digit SOC code. This way, we can classify managers into Executives (SOC "11-1"), Marketing and Sales managers (SOC "11-2"), Operations managers (SOC "11-3"), and Other (SOC "11-9") group comprising of some relatively smaller more granular categories as well as managerial positions that could not be classified. The results in Appendix Table A3 show that there is no a specific managerial category that significantly increases in demand relative to other categories, as the changes in all category shares relative to the total managerial vacancies are not statistically significant. This suggests that the demand for managers grows across all types of managerial

[5]The results are consistent if in the regressions with *AI Managers Share* we drop companies with zero vacancies for AI Managers, even though, again, the F-statistics is significantly smaller in such regressions due to lower number of observations (not tabulated).

roles. We obtain qualitatively consistent results when we run the same analysis using 5-digit SOC classifications, with the only exception that the share of vacancies for Architectural and Engineering Managers (SOC code "11-904") is increasing relative to the total number of managerial vacancies when firms adopt AI more intensively. In general, managers are becoming equally more important across all the functions of the organization.

4.2. AI Adoption and the Demand for Managerial Skills

Next, we are interested in understanding how AI adoption may transform the role of managers within the firm. In other words, do managers need the same skills as before, or given the AI-driven change taking place within the organization, managerial tasks evolve as well?

Table 7 and Figure 2 report how AI adoption affects specific managerial skills.[6] The analysis reveals that AI adoption leads to an increased demand for cognitive and interpersonal skills, such as Teamwork / Collaboration, Creativity, and Data Analysis. In addition, there's a clear decline in demand for traditional managerial skills like Scheduling, Microsoft Office, and Budgeting. The table underscores how AI reshapes the demand for managerial jobs by increasing the importance of skills allowing to solve more complex problems while diminishing the need for routine administrative capabilities.

Figure 3 focuses on the later sub-period of accelerated AI adoption from 2016 to 2022. It shows that the same skills — Teamwork / Collaboration, Creativity, and Stakeholder Management — remain highly demanded in managerial positions. Interestingly, sales-related expertise becomes more significant, under different skill labels such as Product Sales, Sales Management and Sales Goals. This result speaks to Babina et al. (2024) on the impact of AI adoption on firm growth. Skills decreasing in importance are also consistent between the periods - Customer Service and Contact, Budgeting, Multi-tasking, Microsoft-powered tools

[6] Only the most affected skills are presented, according to IV regressions in column (3) in Table 7.

- are less required in this later period. Overall, the changes in the demand for skills suggest that, as AI becomes more embedded in business processes, managerial roles increasingly emphasize problem-solving capabilities and skills facilitating firm growth, rather than skills needed in technical and routine tasks.

Appendix Table A8 presents detailed regression results for the top 100 most required skills in managerial jobs. Supplementing the above results, the table provides granular evidence of how AI is reshaping managerial roles by promoting higher-order skills and phasing out more traditional competencies.

4.3. AI Adoption and the Effect on Posted Wages and Overall Vacancies

So far we have documented an increased demand for managers and changes in their skill profile towards more problem-solving capabilities and skills facilitating firm growth. Next, we want to explore the impact on posted wages to see if managers are becoming more valuable within the organization. If managers are expected to deliver increased productivity effects by complementing AI technology, we should expect companies to offer them higher salaries when their *AI Share* is higher. Table 8 reports the change in the level of managerial salaries of AI adoption. Columns (1) and (2) suggests that with one percentage point increase in *AI Share*, managerial salaries offered in the vacancies increase by 1.2% according to the OLS regression (column (1)) and by 7% according to the IV specification (column (2)).

Does this mean that managers are becoming more expensive relatively to other workers of the company? Columns (3) to (6) of Table 8 show that this is not likely to be the case. In fact, both ratios of the average managerial salaries to non-managerial jobs (columns (3) and (4)) and to all non-managerial jobs in professional occupations with 2-digit SOC codes 13-29 and 41-43 (columns (5) and (6)) are not statistically significant. Together, these results suggest that, when companies adopt AI, both managerial and non-managerial salaries grow

with similar rates. Overall, all jobs are becoming more valuable with AI adoption.

Finally, Table 9 examines AI's effect on the overall firm labor demand. In Panel A, we find that AI adoption is associated with a reduction in total vacancies in 2011-2022 period. When *AI Share* increases by one percentage point, there is a decrease by up to 8% in overall postings, a 9% decrease in non-AI vacancies, as well as a 13% decrease in non-AI or non-managerial vacancies. This indicates some potential replacement of labor with AI.

As this result is somewhat in contrast with Acemoglu et al. (2022) and Babina et al. (2024), we analyze further whether this effect of AI is consistent across the earlier and later sub-periods we considered before. Panel B shows that the negative relationship between *AI Share* and vacancies is primarily driven by the earlier part of our data (2011-2015), as the coefficients estimated in the later period of our sample have large standard errors suggesting a lack of clear statistically significant relationship. This evidence suggests that the nature of AI technology could vary over time, with earlier AI technologies primarily targeted at labor substitution.

4.4. Robustness

We conduct a range of robustness tests to ensure that our main results are not driven by outliers or specific measurement techniques for the key variables. Thus, we proceed by adjusting the sample for potential outliers and use alternative measures to show that the key result that *Managers Share* increases with firms' AI adoption is robust across different specifications.

4.4.1. Alternative Variable Definitions

Appendix Table A4 tests the robustness of the relationship between AI adoption and the demand for managers by using alternative methods to identify AI jobs. Panel A uses a keyword-based approach to define AI vacancies, while Panel B employs a continuous measure of *AI Share* (both described in Section 2.1.). Both methods yield similar results: AI

adoption is positively correlated with an increase in managerial vacancies and managerial share, suggesting that the main findings are not sensitive to how AI jobs are defined.

We also verify that our results on a positive effect of AI adoption on the demand for managers are not driven specifically by an increased demand for managers with AI skills, included in the dependent variable estimation. Thus, we drop AI Managers from the number of managerial job postings and from the numerator of *Managers Share* and repeat the analysis in Table A5. We observe that even though the coefficients are becoming slightly smaller due to the decrease in the magnitude of the dependent variables, the relationship between *AI Share* and the demand for managers in absolute and relative terms remains strong. Therefore, the demand for managers grows beyond simply requiring more of managers with AI skills.

4.4.2. Robustness to Sample Adjustments

Appendix Table A6 explores the robustness of the results by making adjustments to the sample aimed at removing outliers. Panel A excludes firms from the finance sector, as it might have different dynamics than other industries, while Panel B excludes the top 5% of firm-years ranked by *AI Share*. The results remain consistent, showing a positive relationship between AI adoption and managerial demand. This confirms that the findings are not driven by the inclusion of financial companies or firms with exceptionally high AI adoption, strengthening our confidence in the key results.

Appendix Table A7 assesses whether the results are biased by potential survivorship bias due to companies entering and leaving the sample. To check this, we use a balanced panel of firms which remain in the sample throughout the entire 2011-2022 period. The positive correlation between AI adoption and managerial demand holds, even when focusing only on firms that consistently report data over time (there 524 such companies). This suggests that the findings are not driven by changes in the sample composition, providing further confidence in the conclusions.

5. What Do AI Managers Do?

We have observed in earlier results that the demand for Managers with AI skills grows even faster than the demand for managers in general when firm adopt more AI. Figure A1 shows that, in general, the demand for managers with AI skills grew rapidly in the analyzed period - it increased from virtually zero to 0.6% of all managerial jobs in 2022, with the largest growth occurring in the past 7 years. Thus, "AI Manager" is a relatively recent phenomenon and it is worth understanding what AI managers do in companies.

We take a skill-based perspective to explore how distinct AI manager profiles are relative to other type of managers and to AI specialists in IT jobs (2-digit SOC code 15). Table 10 presents the top 20 most frequently required skills for managers overall, for AI managers, and for AI specialists in IT. The lists of skills show that AI managers' profile reflects an AI specialist with substantial managerial capabilities. Generally, AI specialists in IT require highly technical skills (Machine Learning, Python, Data Science are top-3 skills), while AI managers, just like general managers, focus a lot on Teamwork, Collaboration, and Communication. AI Managers are also expected to be skilled in Product Management and People Management, that are typically not found among top skills of AI specialists. Thus, the data highlights that while technical expertise is crucial for AI managers, they must also balance these skills with interpersonal and general managerial competencies. This illustrates the complementary nature of technical and managerial tasks in this new role of AI Managers.

6. Conclusion

In this paper, we investigate the impact of AI adoption on the demand for managers and the skills required for managerial roles. Using job postings data from Lightcast, we develop a skill-based measure of AI adoption, tracking firms' AI-related vacancies over time. Our empirical analysis demonstrates that AI adoption significantly increases the demand

for managers, as firms require more managerial oversight to integrate and manage AI systems alongside human teams. Contrary to concerns that AI might reduce managerial needs, our results indicate that firms adopting AI tend to increase both the number and share of managerial positions. Moreover, we find that the effect is stronger when accounting for endogeneity using a Bartik-style instrumental variable, confirming that AI drives a substantive change in firm management structures.

In addition to influencing the quantity of managerial positions, AI adoption reshapes the skill profile of managers. Our analysis reveals that firms increasingly seek managers with cognitive and interpersonal skills, such as collaboration, creativity, and data analysis, while the demand for routine administrative tasks declines. This shift reflects the changing nature of managerial work in AI-driven environments, where managers are required to engage in more complex decision-making and strategic oversight. Furthermore, while AI adoption raises managerial salaries, it does so in a way that reflects broader labor market trends, suggesting that firms value both managerial and non-managerial roles more as they integrate AI. Overall, our findings underscore the profound organizational changes AI brings, particularly in enhancing the strategic importance of managerial expertise.

One of the most challenging aspects of integrating AI into organizations is managing the interface between human and AI workers. AI systems are prone to algorithmic bias, fairness issues, and accountability challenges, all of which require managerial oversight. Dell'Acqua et al. (2023) highlight the need for human intervention to mitigate these issues, as managers will be responsible for ensuring that AI is used ethically and does not negatively impact the workforce. Furthermore, the interaction between human and AI workers can create coordination challenges that require mediation. Managers will need to address potential conflicts arising from this interaction, ensuring that AI systems enhance human performance rather than disrupt it. This additional layer of responsibility suggests that managers will be essential in navigating the human-AI interface, further increasing the need for human

managers in an AI-augmented workforce.

Contrary to the common narrative that AI will lead to a reduction in management layers, the process of AI integration itself might actually increase managerial intensity. The need for more nuanced oversight, the complexity of managing the human-AI interface, and the interpretation of AI outputs all contribute to this likelihood. Dessein, Garicano and Gertner (2010) argue that integrating new technologies, particularly those that create synergies between different parts of an organization, often necessitates hybrid organizational structures that combine functional and business-unit management. In this context, AI could be viewed as a new functional unit that requires specialized managerial oversight, adding to the number of managers necessary to ensure smooth operations. This increase in complexity and responsibility means that managers will be required not only to oversee human workers but also to manage the deployment, ethical use, and operational efficiency of AI systems.

Therefore, based on this study of early AI implementation in companies, we expect that the broader integration of AI into the economy is likely to significantly reshape the role of managers, potentially leading to an increase in managerial intensity rather than its reduction. While AI can automate certain tasks, its introduction adds complexity that requires human oversight, interpretation, and coordination. Managers will play a crucial role in ensuring that AI systems operate effectively, align with organizational goals, and are used ethically, particularly at the interface between human and AI workers. This added responsibility suggests that AI, far from reducing the number of managerial positions, leads to an increase in human managers relative to human workers, particularly those managers that are equipped with the skills to navigate the complexities of an AI-augmented workplace. As organizations continue to integrate AI, the demand for skilled managers capable of handling both technical systems and human resources will likely grow, reshaping the landscape of management in the future.

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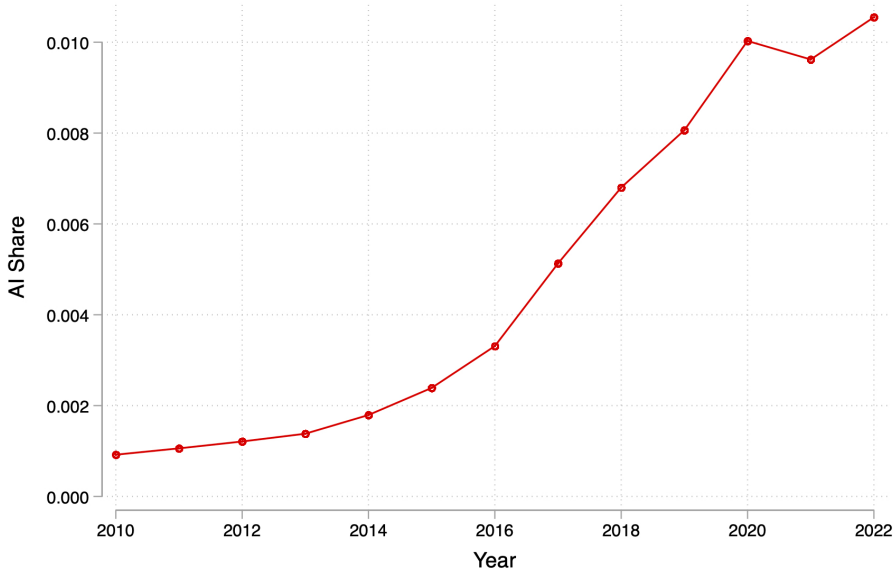
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Figure 1: Share of vacancies demanding AI skills and Managers over time. The figure shows the average percentage of firms' AI-related vacancies in Panel A and the average percentage of firms' vacancies in Management occupation (vacancies in the 2-digit SOC code "11") in Panel B over time.

Panel A: AI Share.



Panel B: Managers Share.

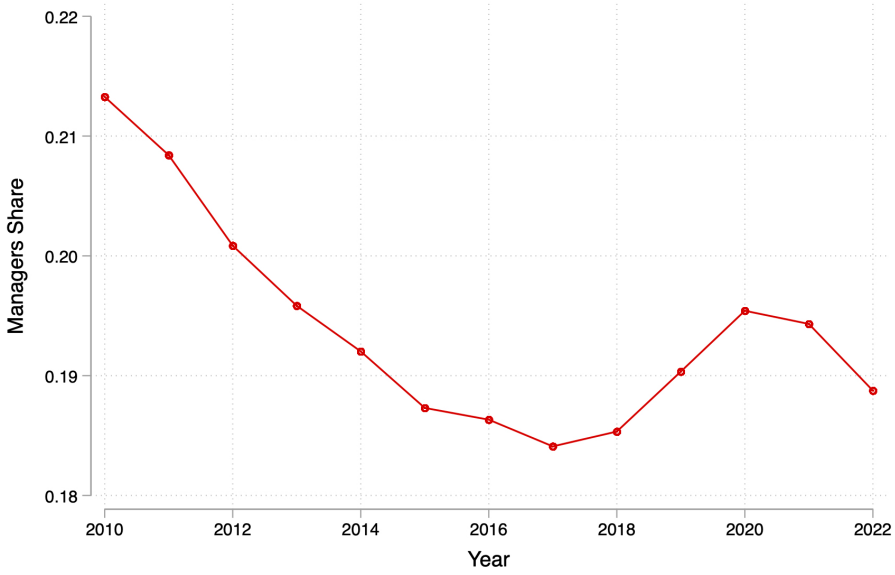


Figure 2: AI Adoption and the Demand for Skills - 2011-2022 Period (Most Affected Skills). The figure shows coefficients estimated in 2SLS regressions following specification 2 with a specific *Managerial Skill Share* as the dependent variable, *AI Share* as the independent variable, and Bartik-style instrument for *AI Share*. In the graph, circles represent the coefficient estimates and horizontal bars represent 95% confidence intervals for them. The data used in these regressions covers the period between 2011 and 2022. The figure only presents the most affected skills in managerial vacancies. The results for the full list of top-100 most frequent skills in managerial vacancies are presented in Table A8. All coefficient estimates are multiplied by a 100 to aid the interpretation of the results (each coefficient can be directly interpreted as a percentage point change in an analyzed skill share with a percentage-point change in *AI Share*).

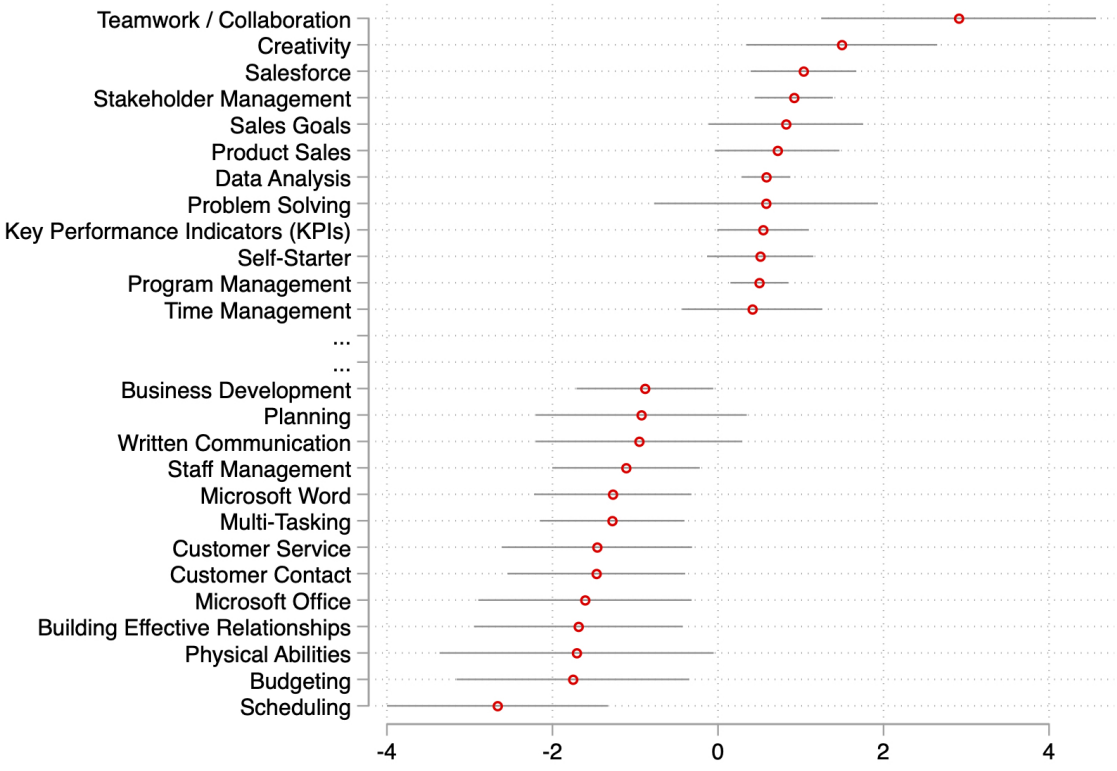


Figure 3: AI Adoption and the Demand for Skills - 2016-2022 Period (Most Affected Skills). The figure shows coefficients estimated in 2SLS regressions following specification 2 with a specific *Managerial Skill Share* as the dependent variable, *AI Share* as the independent variable, and Bartik-style instrument for *AI Share*. In the graph, circles represent the coefficient estimates and horizontal bars represent 95% confidence intervals for them. The data used in these regressions covers the period between 2016 and 2022. The figure only presents the most affected skills in managerial vacancies. The results for the full list of top-100 most frequent skills in managerial vacancies are presented in Table A8. All coefficient estimates are multiplied by a 100 to aid the interpretation of the results (each coefficient can be directly interpreted as a percentage point change in an analyzed skill share with a percentage-point change in *AI Share*).

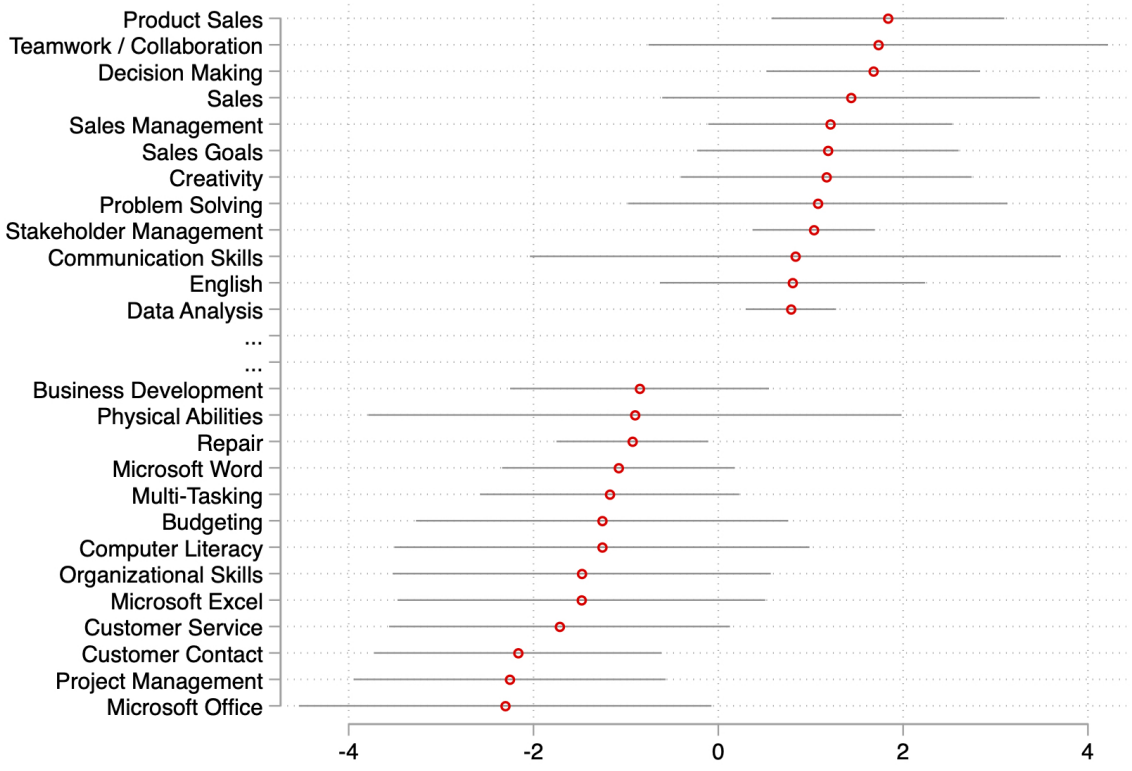


Table 1: Summary statistics. The sample includes matched Compustat-Lightcast data, with each observation at the company-year level. All ratios are winsorized at 1% and 99%. IT companies, companies that have fewer than 30 managerial vacancies or missing data for variables used in the analysis, and companies that appear in the sample only once are excluded. Summary statistics for all top-100 skills in managerial vacancies are presented in Table A2.

	N co.	N obs.	Mean	SD	p(5)	p(95)
Vacancies-based Characteristics:						
AI Share	2,322	16,021	0.5%	1.3%	0.0%	2.6%
AI Share (2011-2015)	1,643	5,866	0.1%	0.4%	0.0%	0.8%
AI Share (2016-2022)	2,062	10,155	0.7%	1.6%	0.0%	3.6%
AI Share (Keywords-based)	2,322	16,021	0.7%	1.5%	0.0%	3.3%
N Vacancies	2,322	16,021	4,001	12,977	149	16,513
Ln(Vacancies)	2,322	16,021	7.01	1.44	5.00	9.71
Managerial vacancies:						
N Managerial vacancies	2,322	16,021	510	1,567	35	2,017
Ln(Managerial vacancies)	2,322	16,021	5.15	1.26	3.56	7.61
Managers Share	2,322	16,021	19.1%	11.6%	4.3%	42.2%
Managers Share (2011-2015)	1,643	5,866	19.5%	11.3%	5.0%	40.9%
Managers Share (2016-2022)	2,062	10,155	18.8%	11.8%	4.0%	42.9%
AI Managers:						
N AI Managers	2,322	16,021	4	65	0.0	7
AI Managers Share	2,322	16,021	0.3%	0.9%	0.0%	1.7%
AI Managers Share (Keywords-based)	2,322	16,021	0.4%	1.3%	0.0%	2.5%
Skill Shares within Managerial vacancies:						
Communication Skills	2,322	16,021	49.6%	20.9%	11.6%	84.1%
Budgeting	2,322	16,021	29.7%	17.5%	4.1%	62.6%
Planning	2,322	16,021	27.8%	15.6%	3.2%	55.6%
Teamwork / Collaboration	2,322	16,021	27.6%	19.2%	1.8%	64.1%
Project Management	2,322	16,021	22.3%	14.8%	1.1%	48.8%
Scheduling	2,322	16,021	18.4%	15.2%	1.6%	49.7%
Problem Solving	2,322	16,021	23.0%	16.3%	1.6%	54.3%
Microsoft Excel	2,322	16,021	23.5%	17.1%	2.3%	58.0%
Organizational Skills	2,322	16,021	19.1%	14.9%	2.1%	49.3%
Microsoft Office	2,322	16,021	19.4%	17.1%	0.9%	49.3%
Control Variables:						
Software Share	2,322	16,021	0.29	0.20	2.1%	65.8%
Sales	2,322	16,021	12,211	31,417	173	53,270
Ln(Sales)	2,322	16,021	7.89	1.80	5.02	10.74
Employment	2,322	16,021	30.86	88.45	0.48	125.10
Ln(Employment)	2,322	16,021	2.12	1.68	-0.74	4.83
Cash/Assets	2,322	16,021	13.9%	16.9%	0.6%	53.6%
R&D/Sales	2,322	16,021	13.7%	82.9%	0.0%	28.0%

Table 2: Change in Vacancy-based Characteristics. The table presents the descriptive statistics for some of the analyzed variables to showcase their change over time. The table presents the averages of variables in 2011 (column (1)), 2016 (column (2)), and 2022 (column (3)), as well as shows their change between 2011 and 2016 and 2016 and 2022 in columns (4) and (5), respectively. The sample includes matched Compustat-Lightcast data, with each observation at the company-year level. All ratios are winsorized at 1% and 99%. IT companies, companies that have fewer than 30 managerial vacancies or missing data for variables used in the analysis, and companies that appear in the sample only once are excluded.

	Mean			Change	
	2011	2016	2022	2011/16	2016/22
	(1)	(2)	(3)	(4)	(5)
Vacancies-based Characteristics:					
AI Share	0.1%	0.3%	1.0%	0.2%	0.7%
AI Share (Keywords-based)	0.2%	0.4%	1.2%	0.2%	0.9%
Vacancies	2,589	4,345	5,438		
Ln(Vacancies)	6.77	7.06	7.26		
AI Managers:					
AI Managers Share	0.0%	0.1%	0.5%	0.1%	0.4%
AI Managers Share (Keywords-based)	0.1%	0.2%	0.9%	0.1%	0.7%
Managerial vacancies:					
N Managerial vacancies	426	520	780		
Ln(Managerial vacancies)	5.03	5.17	5.39		
Managers Share	20.8%	18.5%	18.8%	-2.3%	0.3%
Skill Shares within Managerial vacancies:					
Communication Skills	44.0%	49.8%	52.6%	5.8%	2.8%
Budgeting	26.9%	30.0%	29.9%	3.1%	-0.1%
Planning	24.5%	27.7%	29.9%	3.3%	2.2%
Teamwork / Collaboration	17.5%	25.7%	36.1%	8.2%	10.3%
Project Management	20.7%	22.1%	23.9%	1.4%	1.8%
Scheduling	15.2%	18.7%	20.1%	3.5%	1.5%
Problem Solving	18.0%	22.5%	26.2%	4.5%	3.7%
Microsoft Excel	19.4%	23.9%	25.1%	4.4%	1.2%
Organizational Skills	16.4%	19.0%	21.1%	2.6%	2.1%
Microsoft Office	14.2%	19.2%	22.1%	5.0%	2.9%

Table 3: AI Adoption and the Demand for Managers. The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies (SOC code of vacancies = 11) in columns (1) and (2); and *Managers Share* in columns (3) and (4). The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.024	0.072	0.004	0.014
	(0.004)	(0.021)	(0.001)	(0.004)
Software Skills Share	0.629	0.558	0.074	0.057
	(0.057)	(0.072)	(0.010)	(0.013)
Ln(Sales)	0.054	0.089	0.007	0.010
	(0.012)	(0.019)	(0.003)	(0.004)
Ln(Employment)	0.105	0.087	0.012	0.010
	(0.021)	(0.025)	(0.004)	(0.005)
Cash/Assets	0.044	0.032	0.005	0.008
	(0.056)	(0.071)	(0.010)	(0.013)
R&D/Sales	0.018	0.029	0.001	0.001
	(0.007)	(0.019)	(0.002)	(0.004)
Ln(Vacancies)	-0.019	-0.039	-0.003	-0.005
	(0.049)	(0.053)	(0.009)	(0.009)
Observations	15,977	13,331	15,977	13,331
R-squared	0.953		0.829	
F-stat for weak IV		87.10		87.10
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table 4: AI Adoption and the Demand for Managers - by Subperiods. The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies (SOC code of vacancies = 11) in columns (1) and (2); and *Managers Share* in columns (3) and (4). The sample includes matched Compustat-Lightcast data, with each observation at the company-year level. The sample is split into subperiods 2011-2015 (Panel A) and 2016-2022 (Panel B). All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

Panel A: 2011-2015 period

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.040	0.357	0.006	0.045
	(0.017)	(0.147)	(0.003)	(0.026)
Observations	5,613	5,345	5,613	5,345
R-squared	0.964		0.846	
F-stat for weak IV		32.49		32.49
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Panel B: 2016-2022 period

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.015	0.101	0.002	0.023
	(0.005)	(0.033)	(0.001)	(0.006)
Observations	10,049	9,213	10,049	9,213
R-squared	0.965		0.882	
F-stat for weak IV		62.96		62.96
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table 5: AI Adoption and the Demand for Managers - by Industry Sector. The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies (SOC code of vacancies = 11) in Panel A; and *Managers Share* in Panel B. The sample includes matched Compustat-Lightcast data, with each observation at the company-year level. The sample is split into industry sectors based on 2-digit NAICS codes: Manufacturing includes NAICS code 31, Finance includes codes 52 (Finance and Insurance) and 53 (Real Estate), Trade includes codes 42 (Wholesale Trade) and 44 (Retail Trade), and Other includes the remaining 2-digit codes. All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

Panel A: Change in the Number of Managerial Vacancies

	Ln(Managerial vacancies)							
	Manufacturing		Finance		Trade		Other	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI Share	0.030	0.123	0.007	0.040	0.015	-0.064	0.031	0.100
	(0.005)	(0.029)	(0.009)	(0.043)	(0.019)	(0.102)	(0.010)	(0.084)
Observations	7,290	6,026	3,179	2,723	1,832	1,511	3,676	3,071
R-squared	0.961		0.968		0.907		0.953	
F-stat for weakIV		40		26.53		5.395		11.85
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: Change in the Managers Share

	Managers Share							
	Manufacturing		Finance		Trade		Other	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI Share	0.005	0.025	0.002	0.009	0.002	-0.005	0.005	0.014
	(0.001)	(0.007)	(0.002)	(0.010)	(0.002)	(0.010)	(0.002)	(0.014)
Observations	7,290	6,026	3,179	2,723	1,832	1,511	3,676	3,071
R-squared	0.855		0.758		0.775		0.783	
F-stat for weakIV		40		26.53		5.395		11.85
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 6: AI Adoption and the Demand for AI Managers. The table presents the regression following equation 1 with the dependent variable equal to the natural logarithm of AI-related managerial vacancies in columns (1) and (2); and *AI Managers Share* in columns (3) and (4), calculated as the number of AI-related managerial vacancies divided by the total number of the firm's vacancies. The main independent variable is *AI Share* adjusted to not include any managerial job postings. The sample includes matched Compustat-Lightcast data, with each observation at the company-year level. The results in columns (3) and (4) are robust to only keeping the sample with at least one AI-related managerial vacancy, as in columns (1) and (2). All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

	Ln(AI Managers vacancies)		AI Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share (excl. Mgt vacancies)	0.095	0.048	0.058	0.123
	(0.014)	(0.047)	(0.005)	(0.017)
Observations	2,686	2,336	15,977	13,331
R-squared	0.774		0.609	
F-stat for weak IV		6.692		28.34
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table 7: AI Adoption and the Change in the Demand for Skills in Managerial Jobs. The table presents the coefficient estimates for *AI Share* following specification 2, where a specific Managerial Skill Share is a dependent variable. Columns (1) and (5) present coefficient estimates in the OLS regressions in 2011-2022 and 2016-2022 periods respectively; columns (3) and (7) present coefficient estimates in the instrumental variable regressions in 2011-2022 and 2016-2022 periods respectively, with the Bartik-style instrument for *AI Share* (described in Section 3.). The table only presents the results for the most affected skills in managerial vacancies in 2011-2022 period, according to IV regressions (results are sorted on column (3)), as well as the respective results for the same skills in other specifications. The results for the full list of top-100 most demanded skills in managerial vacancies are presented in Table A8. All coefficient estimates are multiplied by a 100 to aid the interpretation of the results (each coefficient can be directly interpreted as a percentage point change in an analyzed skill share with a percentage-point change in *AI Share*). Standard errors clustered at the company level are reported in parentheses.

	2011-2022				2016-2022			
	OLS		IV		OLS		IV	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Skills in Increasing Demand:								
Teamwork / Collaboration	0.64	(0.15)	2.91	(0.85)	0.44	(0.17)	1.73	(1.27)
Creativity	0.24	(0.12)	1.49	(0.59)	0.09	(0.12)	1.17	(0.8)
Salesforce	-0.06	(0.05)	1.03	(0.33)	-0.14	(0.06)	0.53	(0.41)
Stakeholder Management	0.25	(0.05)	0.92	(0.24)	0.12	(0.07)	1.03	(0.34)
Sales Goals	-0.14	(0.06)	0.82	(0.48)	-0.17	(0.06)	1.19	(0.72)
Product Sales	0.05	(0.07)	0.72	(0.38)	0.08	(0.07)	1.84	(0.64)
Data Analysis	0.14	(0.04)	0.58	(0.15)	0.09	(0.04)	0.79	(0.25)
Problem Solving	-0.23	(0.16)	0.58	(0.69)	-0.24	(0.15)	1.08	(1.05)
Key Performance Indicators (KPIs)	0.17	(0.07)	0.54	(0.28)	0.11	(0.1)	0.57	(0.47)
Self-Starter	0.08	(0.08)	0.51	(0.33)	0.10	(0.08)	0.42	(0.51)
Program Management	0.12	(0.05)	0.50	(0.18)	0.14	(0.05)	0.59	(0.3)
Time Management	-0.20	(0.07)	0.41	(0.43)	-0.14	(0.08)	0.72	(0.67)
Panel B: Skills in Decreasing Demand:								
Planning	-0.51	(0.12)	-0.93	(0.65)	-0.40	(0.14)	-0.17	(1.02)
Written Communication	-0.20	(0.11)	-0.95	(0.64)	-0.21	(0.12)	-0.33	(0.98)
Staff Management	-0.30	(0.07)	-1.11	(0.45)	-0.18	(0.06)	-0.75	(0.67)
Microsoft Word	-0.48	(0.08)	-1.27	(0.48)	-0.34	(0.08)	-1.08	(0.64)
Multi-Tasking	-0.28	(0.09)	-1.28	(0.45)	-0.15	(0.09)	-1.18	(0.72)
Customer Service	-0.46	(0.1)	-1.46	(0.59)	-0.37	(0.1)	-1.72	(0.94)
Customer Contact	-0.29	(0.08)	-1.47	(0.55)	-0.13	(0.07)	-2.17	(0.79)
Microsoft Office	-0.88	(0.11)	-1.61	(0.66)	-0.74	(0.13)	-2.31	(1.14)
Building Effective Relationships	-0.60	(0.11)	-1.69	(0.64)	-0.37	(0.12)	-0.44	(1.06)
Physical Abilities	-0.62	(0.11)	-1.71	(0.84)	-0.44	(0.12)	-0.90	(1.47)
Budgeting	-0.71	(0.14)	-1.75	(0.72)	-0.36	(0.14)	-1.26	(1.03)
Scheduling	-0.71	(0.11)	-2.67	(0.68)	-0.43	(0.12)	-0.74	(0.94)

Table 8: AI Adoption and Salaries. The table presents the regression results with the following dependent variables: the natural logarithm of average salaries offered in job postings in managerial vacancies in columns (1) and (2); the ratio of average salaries offered in managerial vacancies to average salaries offered in all non-managerial vacancies in columns (3) and (4); and the ratio of average salaries offered in managerial vacancies to average salaries offered in all non-managerial vacancies within firms' Professional occupations (2-digit SOC codes 13-29 and 41-43) in columns (5) and (6). The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. Only companies with non-missing salary information are included in the regressions. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

	Log(Mgt Salary)		Ratio of Mgt to Non-Mgt Salaries		Ratio of Mgt to Non-Mgt (Prof) Salaries	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share	0.012	0.068	0.003	0.010	0.004	-0.017
	(0.005)	(0.029)	(0.010)	(0.053)	(0.010)	(0.049)
Observations	11,112	9,091	10,896	8,911	10,752	8,787
R-squared	0.450		0.285		0.281	
F-stat for weak IV		92.91		81.21		80.43
Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Table 9: AI Adoption and Company Employment. The table presents regression results with the following dependent variables: the natural logarithm of the total number of firms' vacancies in columns (1) and (2); the natural logarithm of the total number of firms' non-AI-related vacancies in columns (3) and (4); and the natural logarithm of the total number of firms' non-AI-related and non-managerial vacancies in columns (5) and (6). Panel A presents results for 2011-2022 period, while Panel B shows results of the same specifications in the 2016-2022 sample. The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

Panel A: 2011-2022 Period.

	Ln(Vacancies)		Ln(Non-AI Vacancies)		Ln(Non-AI or Non-Mgt Vacancies)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share	-0.019	-0.076	-0.032	-0.090	-0.042	-0.119
	(0.010)	(0.041)	(0.010)	(0.041)	-0.01	-0.044
Observations	15,977	13,331	15,977	13,331	15,977	13,331
R-squared	0.890		0.890		0.89	
F-stat for weak IV		89.03		89.03		89.03
Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Panel B: 2016-2022 Period.

	Ln(Vacancies)		Ln(Non-AI Vacancies)		Ln(Non-AI or Non-Mgt Vacancies)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share	0.024	0.073	0.012	0.061	0.005	0.024
	(0.010)	(0.055)	(0.010)	(0.055)	(0.010)	(0.060)
Observations	10,049	9,213	10,049	9,213	10,049	9,213
R-squared	0.927		0.927		0.928	
F-stat for weak IV		63.33		63.33		63.33
Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

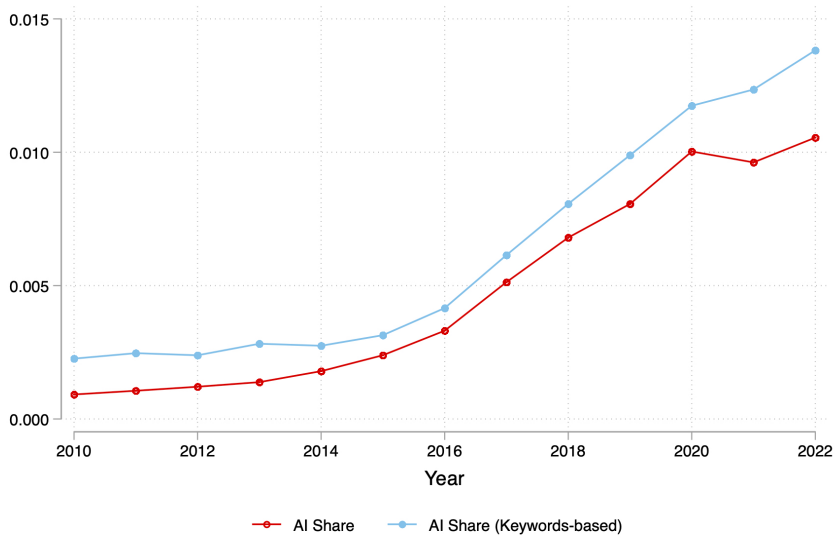
Table 10: AI Managers' Skillset. The Table presents 20 most frequently mentioned skills in Management occupations (2-digit SOC code 11) (column (1)), in managerial vacancies also demanding AI skills (column (2)), and in IT vacancies (2-digit SOC code 15) requiring AI skills. Bold font highlights management-related skills. Data includes 2022 vacancies of Compustat-matched firms that were included in the final sample (e.g., IT companies excluded).

Managers	AI Managers	AI Specialists in IT
(1)	(2)	(3)
Communication Skills	Machine Learning	Machine Learning
Teamwork / Collaboration	**Teamwork / Collaboration**	Python
Planning	Artificial Intelligence	Data Science
Problem Solving	**Communication Skills**	**Teamwork / Collaboration**
Budgeting	Python	SQL
Project Management	Big Data	Artificial Intelligence
Microsoft Excel	Data Science	Software Engineering
Scheduling	Data Engineering	Java
Building Effective Relationships	**Product Management**	**Communication Skills**
Organizational Skills	Java	Big Data
Microsoft Office	Software Engineering	**Research**
Customer Service	**People Management**	Software Development
Writing	SQL	**Problem Solving**
Detail-Oriented	**Problem Solving**	Scala
Research	Software Development	Apache Hadoop
Creativity	**Research**	C++
Leadership	Data Warehousing	Pipeline (Computing)
Sales	Analytical Skills	Data Engineering
Written Communication	NoSQL	Data Analysis
Microsoft Powerpoint	**Mentoring**	Deep Learning

A Appendix

Figure A1: Share of vacancies demanding AI skills over time, overall and within managerial occupations. The figure shows the average percentage of firms' AI-related vacancies (Panel A) and the average percentage of firms' AI vacancies within Management occupation (Panel B) over time. The graphs compare the *AI Shares* estimated using the core method of the analysis and a keywords-based approach to define AI-related vacancies. The list of keywords used for the keywords-based approach are presented in Table A1.

Panel A: Overall AI Share.



Panel B. AI Managers Share.

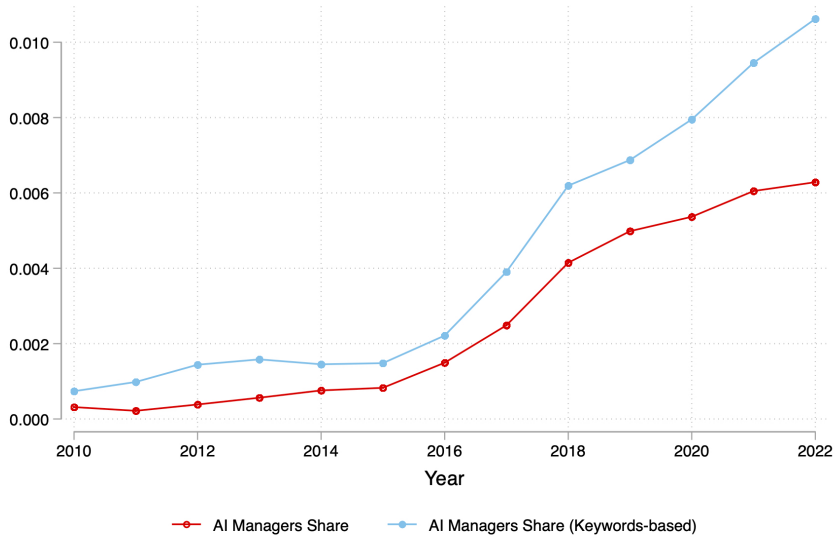
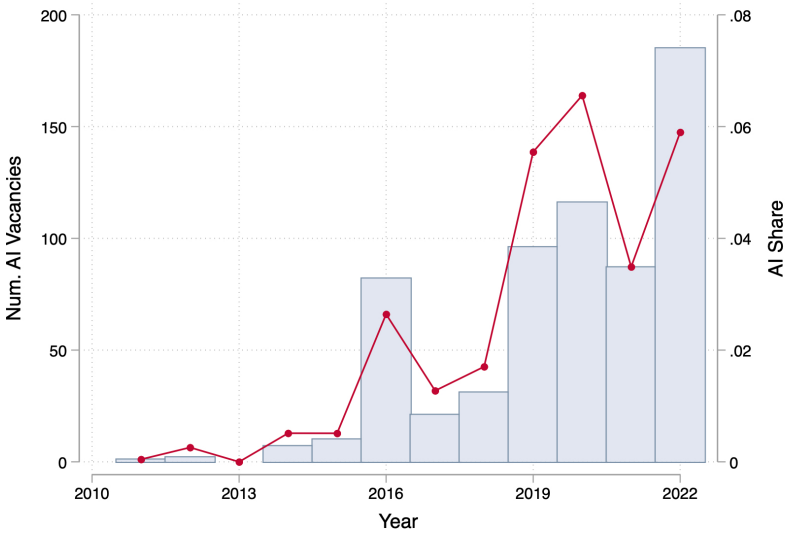


Figure A2: Case-study - PROCTER & GAMBLE CO.

Panel A: AI Hiring.



Panel B. Structure of AI Hiring by Occupations.

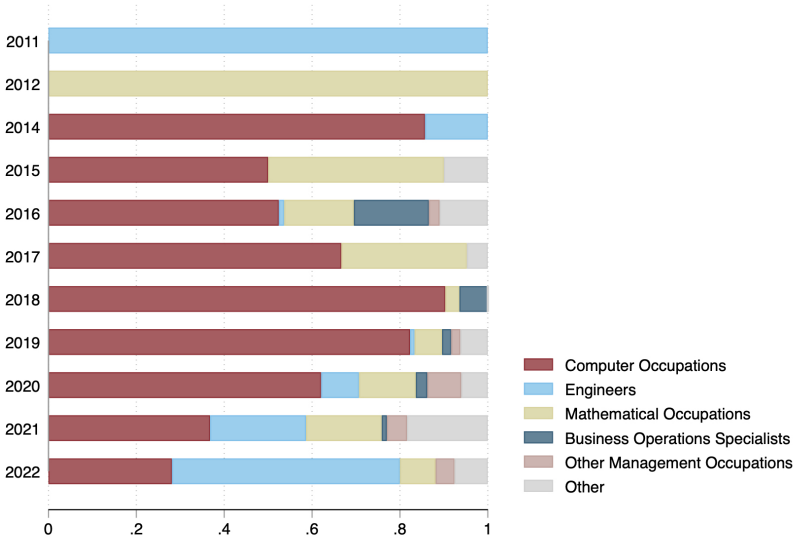
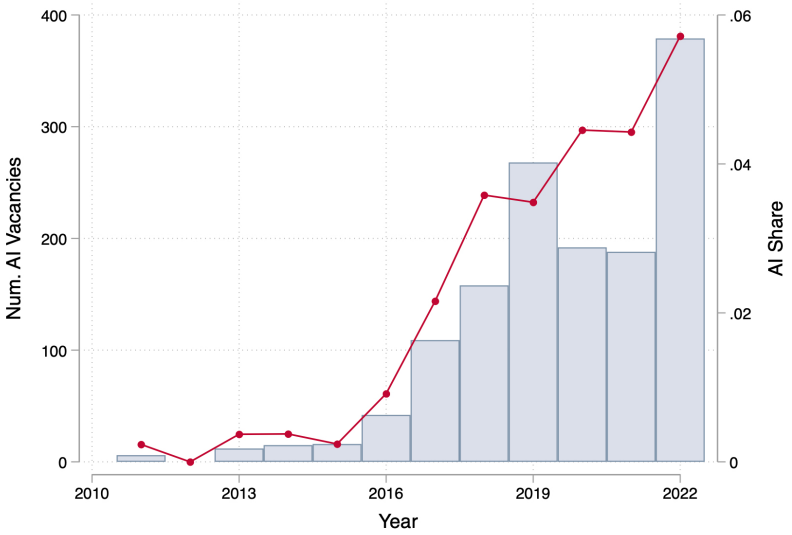


Figure A3: Case-study - Amgen.

Panel A: AI Hiring.



Panel B. Structure of AI Hiring by Occupations.

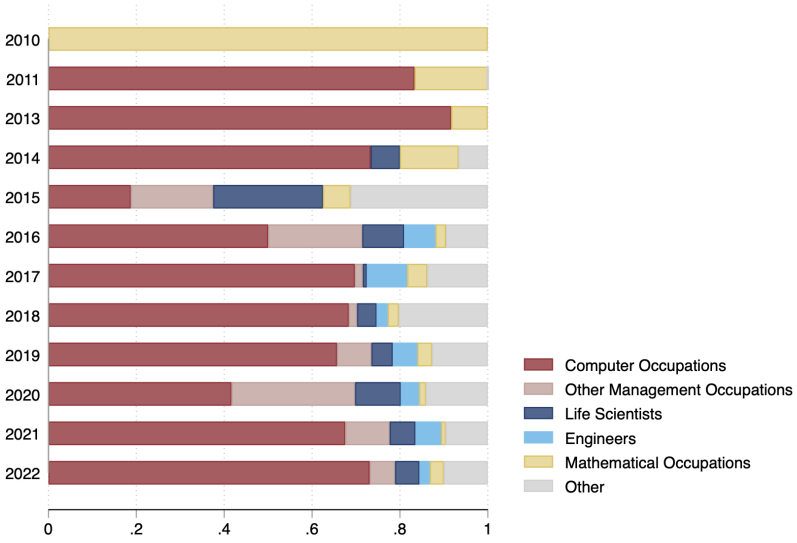


Table A1: List of AI Skills List of skills in the Burning Glass Technologies job vacancies dataset used to identify AI vacancies.

N	Skill	N	Skill
1	AI ChatBot	37	Mlpy
2	AI KIBIT	38	Modular Audio Recognition Framework
3	ANTLR	39	MoSes
4	Apertium	40	MXNet
5	Artificial Intelligence	41	Natural Language Processing
6	Automatic Speech Recognition	42	Natural Language Toolkit (NLTK)
7	Caffe Deep Learning Framework	43	ND4J (software)
8	Chatbot	44	Nearest Neighbor Algorithm
9	Computational Linguistics	46	Object Recognition
10	Computer Vision	47	Object Tracking
11	Decision Trees	48	OpenCV
12	Deep Learning	49	OpenNLP
13	Deeplearning4j	50	Pattern Recognition
14	Distinguo	51	Pybrain
15	Google Cloud ML Platform	45	Neural Networks
16	Gradient boosting	52	Random Forests
17	H2O (software)	53	Recommender Systems
18	IBM Watson	54	Semantic Driven Subtractive Clustering
19	Image Processing	55	Semi-Supervised Learning
20	Image Recognition	56	Sentiment Analysis / Opinion Mining
21	IPSoft Amelia	57	Sentiment Classification
22	Ithink	58	Speech Recognition
23	Keras	59	Supervised Learning (ML)
24	Latent Dirichlet Allocation	60	Support Vector Machines (SVM)
25	Latent Semantic Analysis	61	TensorFlow
26	Lexalytics	62	Text Mining
27	Lexical Acquisition	63	Text to Speech (TTS)
28	Lexical Semantics	64	Tokenization
29	Libsvm	65	Torch (Machine Learning)
30	Machine Learning	66	Unsupervised Learning
31	Machine Translation (MT)	67	Virtual Agents
32	Machine Vision	68	Vowpal
33	Madlib	69	Wabbit
34	Mahout	70	Word2Vec
35	Microsoft Cognitive Toolkit	71	Xgboost
36	MLPACK (C++ library)		

Table A2: Summary statistics - Skill Shares within Managerial Vacancies. The sample includes matched Compustat-Lightcast data, with each observation at the company-year level. All ratios are winsorized at 1% and 99%. IT companies, companies that have fewer than 30 managerial vacancies or missing data for variables used in the analysis, and companies that appear in the sample only once are excluded.

Variable	N co.	N obs.	Mean	SD	p(5)	p(95)
Communication Skills	2,322	16,021	49.6%	20.9%	11.6%	84.1%
Budgeting	2,322	16,021	29.7%	17.5%	4.1%	62.6%
Planning	2,322	16,021	27.8%	15.6%	3.2%	55.6%
Teamwork / Collaboration	2,322	16,021	27.6%	19.2%	1.8%	64.1%
Project Management	2,322	16,021	22.3%	14.8%	1.1%	48.8%
Scheduling	2,322	16,021	18.4%	15.2%	1.6%	49.7%
Problem Solving	2,322	16,021	23.0%	16.3%	1.6%	54.3%
Microsoft Excel	2,322	16,021	23.5%	17.1%	2.3%	58.0%
Organizational Skills	2,322	16,021	19.1%	14.9%	2.1%	49.3%
Microsoft Office	2,322	16,021	19.4%	17.1%	0.9%	54.9%
Building Effective Relationships	2,322	16,021	16.5%	13.6%	0.7%	44.4%
Writing	2,322	16,021	12.9%	12.4%	0.0%	35.9%
Staff Management	2,322	16,021	9.7%	10.9%	0.0%	31.5%
Research	2,322	16,021	12.5%	10.5%	0.2%	33.3%
Customer Service	2,322	16,021	13.0%	14.1%	0.0%	43.4%
Sales	2,322	16,021	16.4%	17.1%	0.0%	54.5%
Detail-Oriented	2,322	16,021	13.9%	13.8%	0.0%	42.6%
Creativity	2,322	16,021	11.4%	11.6%	0.0%	34.2%
Computer Literacy	2,322	16,021	13.3%	15.8%	0.0%	47.2%
Written Communication	2,322	16,021	13.2%	13.3%	0.0%	40.2%
Leadership	2,322	16,021	11.1%	10.3%	0.0%	31.1%
Microsoft Powerpoint	2,322	16,021	12.6%	11.6%	0.0%	35.3%
Physical Abilities	2,322	16,021	8.9%	18.8%	0.0%	56.3%
Microsoft Word	2,322	16,021	9.6%	11.7%	0.0%	34.3%
Business Development	2,322	16,021	8.7%	10.2%	0.0%	29.5%
Multi-Tasking	2,322	16,021	8.1%	9.6%	0.0%	26.7%
Accounting	2,322	16,021	7.8%	8.2%	0.0%	23.8%
Presentation Skills	2,322	16,021	9.5%	9.0%	0.0%	27.0%
Quality Assurance and Control	2,322	16,021	7.1%	7.9%	0.0%	23.4%
Supervisory Skills	2,322	16,021	7.5%	10.4%	0.0%	29.6%
Time Management	2,322	16,021	7.4%	9.8%	0.0%	26.2%

Variable	N co.	N obs.	Mean	SD	p(5)	p(95)
Customer Contact	2,322	16,021	7.0%	9.7%	0.0%	25.6%
Quality Management	2,322	16,021	6.7%	7.2%	0.0%	21.1%
Verbal / Oral Communication	2,322	16,021	7.2%	8.5%	0.0%	23.3%
English	2,322	16,021	5.0%	10.9%	0.0%	22.7%
Retail Industry Knowledge	2,322	16,021	6.0%	14.1%	0.0%	39.3%
Sales Management	2,322	16,021	7.3%	11.4%	0.0%	31.6%
People Management	2,322	16,021	5.6%	7.1%	0.0%	19.1%
Analytical Skills	2,322	16,021	7.3%	7.5%	0.0%	22.3%
Mentoring	2,322	16,021	4.8%	6.3%	0.0%	16.2%
Cost Control	2,322	16,021	5.4%	7.0%	0.0%	20.0%
Decision Making	2,322	16,021	6.1%	7.7%	0.0%	20.0%
Strategic Planning	2,322	16,021	5.0%	5.2%	0.0%	15.4%
Meeting Deadlines	2,322	16,021	5.1%	7.4%	0.0%	18.8%
Product Management	2,322	16,021	6.1%	8.7%	0.0%	25.8%
Restaurant Management	2,322	16,021	1.5%	8.4%	0.0%	2.7%
Project Planning and Development Skills	2,322	16,021	4.9%	5.4%	0.0%	15.9%
Operations Management	2,322	16,021	5.1%	7.3%	0.0%	19.3%
Process Improvement	2,322	16,021	5.8%	6.0%	0.0%	17.6%
Self-Starter	2,322	16,021	5.1%	6.4%	0.0%	17.6%
Business Administration	2,322	16,021	4.5%	6.4%	0.0%	16.3%
Performance Appraisals	2,322	16,021	4.5%	7.5%	0.0%	19.0%
Financial Reporting	2,322	16,021	3.6%	5.0%	0.0%	12.8%
Performance Management	2,322	16,021	5.1%	7.1%	0.0%	18.6%
Key Performance Indicators (KPIs)	2,322	16,021	5.3%	6.5%	0.0%	18.8%
Business Planning	2,322	16,021	6.2%	8.0%	0.0%	22.6%
Teaching	2,322	16,021	0.9%	2.5%	0.0%	4.5%
Marketing	2,322	16,021	3.8%	4.8%	0.0%	13.8%
Repair	2,322	16,021	4.2%	7.3%	0.0%	18.6%
Procurement	2,322	16,021	5.3%	6.2%	0.0%	18.2%
Customer Billing	2,322	16,021	2.1%	4.3%	0.0%	9.5%
Product Sales	2,322	16,021	5.5%	9.0%	0.0%	22.9%
Energetic	2,322	16,021	2.1%	4.5%	0.0%	9.8%
Product Development	2,322	16,021	6.6%	8.1%	0.0%	23.6%
Performance Analysis	2,322	16,021	4.2%	7.2%	0.0%	17.6%
Purchasing	2,322	16,021	4.8%	6.7%	0.0%	18.4%

Variable	N co.	N obs.	Mean	SD	p(5)	p(95)
Program Management	2,322	16,021	2.7%	4.6%	0.0%	13.1%
Patient Care	2,322	16,021	0.9%	4.3%	0.0%	3.5%
Sales Goals	2,322	16,021	5.2%	10.0%	0.0%	26.0%
Conflict Management	2,322	16,021	3.3%	5.0%	0.0%	12.9%
Business Process	2,322	16,021	3.8%	4.3%	0.0%	12.5%
Social Media	2,322	16,021	2.2%	3.5%	0.0%	8.8%
Occupational Health and Safety	2,322	16,021	3.7%	7.5%	0.0%	17.7%
Troubleshooting	2,322	16,021	3.7%	4.7%	0.0%	13.5%
Change Management	2,322	16,021	4.0%	4.7%	0.0%	13.3%
Onboarding	2,322	16,021	2.6%	4.5%	0.0%	10.2%
Oral Communication	2,322	16,021	2.9%	4.9%	0.0%	11.3%
Business Acumen	2,322	16,021	4.2%	6.3%	0.0%	16.1%
Market Strategy	2,322	16,021	3.2%	4.5%	0.0%	12.1%
Stakeholder Management	2,322	16,021	3.2%	4.3%	0.0%	12.1%
Listening	2,322	16,021	2.9%	5.9%	0.0%	12.1%
Financial Analysis	2,322	16,021	3.6%	4.7%	0.0%	12.4%
Spreadsheets	2,322	16,021	3.1%	6.0%	0.0%	13.5%
Negotiation Skills	2,322	16,021	4.1%	5.3%	0.0%	14.4%
Critical Thinking	2,322	16,021	2.4%	4.1%	0.0%	9.9%
Microsoft Project	2,322	16,021	3.0%	4.3%	0.0%	12.0%
Financial Management	2,322	16,021	1.6%	2.9%	0.0%	6.7%
Positive Disposition	2,322	16,021	1.9%	5.0%	0.0%	8.6%
Risk Management	2,322	16,021	2.7%	4.9%	0.0%	12.5%
Prioritizing Tasks	2,322	16,021	2.7%	4.6%	0.0%	11.0%
Legal Compliance	2,322	16,021	2.9%	4.5%	0.0%	11.5%
Editing	2,322	16,021	1.7%	2.8%	0.0%	6.9%
Bilingual	2,322	16,021	1.5%	4.0%	0.0%	7.2%
Employee Training	2,322	16,021	2.3%	5.4%	0.0%	10.9%
Inventory Management	2,322	16,021	2.9%	5.8%	0.0%	13.5%
Spanish	2,322	16,021	1.6%	3.7%	0.0%	7.9%
Data Analysis	2,322	16,021	2.2%	3.0%	0.0%	8.3%
Salesforce	2,322	16,021	2.2%	5.0%	0.0%	11.9%
SAP	2,322	16,021	4.7%	8.6%	0.0%	24.6%
Training Programs	2,322	16,021	2.3%	3.7%	0.0%	9.0%

Table A3: AI Adoption and the Demand for Managers - By Management Category. The table presents the regression results similar to equation 2 with the dependent variable equal to the share of a specific managerial category relative to the number of total managerial vacancies. Thus, it tries to answer, which types of managers are becoming relatively more important. Each management category is defined based on the first 3 digits of the vacancy's SOC, where "Executives" are managerial vacancies with the SOC = "11-1000", "Marketing and Sales" are managerial vacancies with the SOC = "11-2000", "Operations Managers" are managerial vacancies with the SOC = "11-3000", and "Other Managers" are managerial vacancies with the SOC = "11-9000". The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

	Executives Share		Marketing and Sales Share		Operations Managers		Other Managers	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI Share	0.000	-0.001	0.004	-0.005	-0.003	-0.005	-0.001	0.009
	(0.001)	(0.004)	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)
Observations	15,977	13,331	15,977	13,331	15,977	13,331	15,977	13,331
R-squared	0.754		0.790		0.771		0.839	
F-stat for weak IV		87.10		87.10		87.10		87.10
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Table A4: AI Adoption and the Demand for Managers - Robustness to Using Alternative Definitions of AI Jobs. The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies (SOC code of vacancies = 11) in columns (1) and (2); and *Managers Share* in columns (3) and (4). The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. Panel A presents the results for regressions using keywords-based *AI Share*, Panel B shows the results using the continuous measure of *AI Share*. All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3., the IV is adjusted to follow the same approach (keywords or continuous) to estimate the economy-wide industry-specific AI adoption rates. Standard errors clustered at the company level are reported in parentheses.

Panel A: Keywords-based Measure of AI

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Keywords-based AI Share	0.019	0.062	0.003	0.012
	(0.004)	(0.019)	(0.001)	(0.004)
Observations	15,977	13,331	15,977	13,331
R-squared	0.953		0.829	
F-stat for weak IV		81.14		81.14
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Panel B: Continuous Measure of AI Share

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Continuous AI Share	0.122	0.326	0.019	0.066
	(0.017)	(0.092)	(0.003)	(0.018)
Observations	15,977	13,331	15,977	13,331
R-squared	0.953		0.830	
F-stat for weak IV		84.02		84.02
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table A5: AI Adoption and the Demand for Managers - Robustness to Excluding AI Managers. The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies, excluding AI-related ones, in columns (1) and (2); and *Managers Share*, also excluding any AI-related managerial vacancies from the numerator of the ratio, in columns (3) and (4). The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.017	0.063	0.002	0.013
	(0.004)	(0.022)	(0.001)	(0.004)
Observations	15,977	13,331	15,977	13,331
R-squared	0.952		0.829	
F-stat for weak IV		87.10		87.10
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table A6: AI Adoption and the Demand for Managers - Robustness to Sample Adjustments. The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies (SOC code of vacancies = 11) in columns (1) and (2); and *Managers Share* in columns (3) and (4). The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. Panel A presents the results for the sample excluding Finance sector, Panel B shows the results for the sample excluding top AI adopters (top-5% of observations ranked by the *AI Share*). All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

Panel A: Excluding Finance Sector

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.028	0.075	0.004	0.015
	(0.004)	(0.025)	(0.001)	(0.005)
Observations	13,487	11,175	13,487	11,175
R-squared	0.949		0.839	
F-stat for weak IV		59.97		59.97
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Panel B: Excluding Top-5% by AI Share

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.046	0.156	0.008	0.033
	(0.008)	(0.051)	(0.001)	(0.010)
Observations	15,145	12,676	15,145	12,676
R-squared	0.951		0.832	
F-stat for weak IV		114		114
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table A7: AI Adoption and the Demand for Managers - Robustness to Using a Balanced Panel of Firms (No Survivorship Bias). The table presents the regression results for equation 1 with the dependent variable equal to the natural logarithm of managerial vacancies (SOC code of vacancies = 11) in columns (1) and (2); and *Managers Share* in columns (3) and (4). The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. The sample only includes companies that were present in the data all years between 2011 and 2022, thus controlling for suvivorship bias. All ratios are winsorized at 1% and 99%. IV specifications use Bartik-style instrument described in Section 3. Standard errors clustered at the company level are reported in parentheses.

	Ln(Managerial vacancies)		Managers Share	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.024	0.061	0.003	0.010
	(0.006)	(0.023)	(0.001)	(0.004)
Observations	6,288	6,264	6,288	6,264
R-squared	0.954		0.796	
F-stat for weak IV		63.31		63.31
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table A8: AI Adoption and the Change in the Demand for Skills in Managerial Jobs - Top-100 Skills. The table presents the coefficient estimates for *AI Share* following specification 2, where a specific *Managerial Skill Share* is a dependent variable. Columns (1) and (5) present coefficient estimates in the OLS regressions in 2011-2022 and 2016-2022 periods respectively; columns (3) and (7) present coefficient estimates in the instrumental variable regressions in 2011-2022 and 2016-2022 periods respectively, with the Bartik-style instrument for *AI Share* (described in Section 3.). The table presents the results by sorting on the magnitude of the coefficient in column (3). All coefficient estimates are multiplied by a 100 to aid the interpretation of the results (each coefficient can be directly interpreted as a percentage point change in an analyzed skill share with a percentage-point change in *AI Share*). Standard errors clustered at the company level are reported in parentheses.

	2011-2022				2016-2022			
	OLS		IV		OLS		IV	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
Teamwork / Collaboration	0.64	(0.15)	2.91	(0.85)	0.44	(0.17)	1.73	(1.27)
Creativity	0.24	(0.12)	1.49	(0.59)	0.09	(0.12)	1.17	(0.8)
Salesforce	-0.06	(0.05)	1.03	(0.33)	-0.14	(0.06)	0.53	(0.41)
Stakeholder Management	0.25	(0.05)	0.92	(0.24)	0.12	(0.07)	1.03	(0.34)
Sales Goals	-0.14	(0.06)	0.82	(0.48)	-0.17	(0.06)	1.19	(0.72)
Product Sales	0.05	(0.07)	0.72	(0.38)	0.08	(0.07)	1.84	(0.64)
Data Analysis	0.14	(0.04)	0.58	(0.15)	0.09	(0.04)	0.79	(0.25)
Problem Solving	-0.23	(0.16)	0.58	(0.69)	-0.24	(0.15)	1.08	(1.05)
Key Performance Indicators (KPIs)	0.17	(0.07)	0.54	(0.28)	0.11	(0.1)	0.57	(0.47)
Self-Starter	0.08	(0.08)	0.51	(0.33)	0.10	(0.08)	0.42	(0.51)
Program Management	0.12	(0.05)	0.50	(0.18)	0.14	(0.05)	0.59	(0.3)
Time Management	-0.20	(0.07)	0.41	(0.43)	-0.14	(0.08)	0.72	(0.67)
Product Management	0.65	(0.09)	0.40	(0.3)	0.64	(0.1)	0.75	(0.49)
Sales	-0.17	(0.12)	0.35	(0.65)	-0.23	(0.13)	1.44	(1.04)
Detail-Oriented	-0.06	(0.11)	0.29	(0.51)	-0.03	(0.13)	-0.53	(0.87)
Positive Disposition	-0.05	(0.03)	0.27	(0.19)	0.01	(0.04)	-0.00	(0.39)
Risk Management	-0.04	(0.04)	0.24	(0.21)	-0.07	(0.06)	-0.05	(0.35)
Restaurant Management	0.04	(0.03)	0.19	(0.19)	0.03	(0.03)	0.33	(0.36)

	2011-2022				2016-2022			
	OLS		IV		OLS		IV	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Energetic	-0.01	(0.05)	0.14	(0.2)	-0.05	(0.06)	-0.44	(0.37)
Listening	-0.09	(0.05)	0.13	(0.3)	-0.11	(0.06)	0.63	(0.57)
Procurement	-0.10	(0.05)	0.12	(0.25)	-0.10	(0.06)	0.02	(0.37)
Critical Thinking	0.15	(0.05)	0.09	(0.18)	0.11	(0.07)	0.28	(0.3)
Onboarding	-0.04	(0.05)	0.09	(0.2)	-0.12	(0.07)	-0.28	(0.35)
Oral Communication	-0.07	(0.05)	0.03	(0.24)	-0.06	(0.05)	-0.05	(0.38)
People Management	-0.05	(0.07)	0.00	(0.29)	-0.05	(0.08)	0.49	(0.5)
Presentation Skills	0.03	(0.09)	-0.01	(0.35)	0.08	(0.12)	-0.31	(0.64)
Decision Making	-0.03	(0.06)	-0.02	(0.4)	0.01	(0.07)	1.68	(0.59)
Business Acumen	0.00	(0.08)	-0.02	(0.3)	0.14	(0.1)	0.36	(0.42)
Spanish	-0.04	(0.03)	-0.02	(0.16)	-0.06	(0.05)	-0.05	(0.25)
Change Management	-0.09	(0.06)	-0.03	(0.22)	0.01	(0.06)	0.27	(0.37)
Spreadsheets	-0.07	(0.03)	-0.03	(0.21)	-0.06	(0.04)	0.29	(0.36)
Employee Training	-0.01	(0.03)	-0.03	(0.22)	-0.00	(0.03)	0.38	(0.41)
Quality Management	-0.15	(0.05)	-0.05	(0.3)	-0.06	(0.06)	-0.50	(0.46)
Verbal / Oral Communication	-0.10	(0.07)	-0.09	(0.36)	-0.01	(0.08)	-0.25	(0.64)
Analytical Skills	-0.07	(0.08)	-0.10	(0.32)	-0.06	(0.09)	0.54	(0.49)
Retail Industry Knowledge	-0.11	(0.07)	-0.10	(0.45)	-0.17	(0.08)	0.40	(0.69)
Patient Care	-0.03	(0.02)	-0.11	(0.11)	-0.03	(0.02)	0.25	(0.17)
Teaching	-0.01	(0.02)	-0.11	(0.1)	-0.01	(0.02)	-0.25	(0.14)
Business Administration	-0.14	(0.05)	-0.12	(0.25)	-0.21	(0.06)	-0.75	(0.47)
Research	0.20	(0.09)	-0.12	(0.4)	0.17	(0.11)	0.66	(0.74)
Social Media	-0.12	(0.04)	-0.12	(0.18)	-0.08	(0.05)	-0.34	(0.37)
Product Development	0.12	(0.08)	-0.12	(0.36)	0.16	(0.09)	-0.38	(0.5)

	2011-2022				2016-2022			
	OLS		IV		OLS		IV	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legal Compliance	-0.09	(0.03)	-0.13	(0.19)	-0.05	(0.04)	-0.05	(0.31)
Training Programs	-0.05	(0.03)	-0.13	(0.16)	-0.03	(0.03)	-0.32	(0.25)
Bilingual	-0.07	(0.03)	-0.14	(0.19)	-0.10	(0.05)	-0.12	(0.21)
English	0.02	(0.06)	-0.15	(0.46)	-0.09	(0.08)	0.80	(0.73)
Customer Billing	-0.07	(0.03)	-0.17	(0.13)	-0.05	(0.03)	0.11	(0.27)
Mentoring	-0.07	(0.07)	-0.17	(0.27)	0.02	(0.07)	0.46	(0.43)
Sales Management	-0.09	(0.07)	-0.18	(0.38)	-0.10	(0.07)	1.21	(0.67)
Market Strategy	-0.00	(0.05)	-0.18	(0.2)	-0.02	(0.05)	-0.49	(0.37)
Prioritizing Tasks	-0.07	(0.04)	-0.19	(0.19)	-0.03	(0.05)	0.04	(0.3)
Repair	-0.18	(0.04)	-0.19	(0.28)	-0.18	(0.05)	-0.93	(0.42)
Financial Management	-0.03	(0.03)	-0.20	(0.13)	-0.03	(0.03)	-0.09	(0.19)
Organizational Skills	-0.35	(0.11)	-0.21	(0.66)	-0.28	(0.13)	-1.48	(1.04)
Inventory Management	-0.07	(0.03)	-0.22	(0.2)	-0.08	(0.04)	0.05	(0.3)
Occupational Health and Safety	-0.14	(0.04)	-0.24	(0.29)	-0.10	(0.04)	0.49	(0.41)
Supervisory Skills	-0.15	(0.05)	-0.24	(0.4)	-0.10	(0.05)	-0.50	(0.66)
Microsoft Project	-0.18	(0.04)	-0.24	(0.18)	-0.13	(0.04)	-0.23	(0.3)
Troubleshooting	-0.12	(0.04)	-0.25	(0.22)	-0.09	(0.05)	-0.68	(0.39)
Purchasing	-0.03	(0.05)	-0.26	(0.26)	-0.01	(0.05)	0.35	(0.43)
Financial Reporting	-0.11	(0.04)	-0.31	(0.23)	-0.12	(0.05)	-0.56	(0.39)
Project Planning and Development Skills	-0.15	(0.05)	-0.32	(0.23)	-0.10	(0.06)	-0.09	(0.38)
Financial Analysis	-0.11	(0.04)	-0.34	(0.21)	-0.08	(0.05)	-0.41	(0.35)
Business Process	-0.10	(0.05)	-0.37	(0.19)	-0.08	(0.06)	-0.34	(0.3)
Performance Analysis	-0.19	(0.04)	-0.37	(0.33)	-0.09	(0.04)	0.53	(0.56)
Quality Assurance and Control	-0.31	(0.06)	-0.38	(0.33)	-0.19	(0.07)	0.02	(0.49)

	2011-2022				2016-2022			
	OLS		IV		OLS		IV	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Communication Skills	-0.42	(0.17)	-0.42	(0.92)	-0.33	(0.19)	0.83	(1.46)
Editing	-0.03	(0.03)	-0.44	(0.12)	0.01	(0.04)	-0.70	(0.24)
Cost Control	-0.26	(0.05)	-0.48	(0.3)	-0.24	(0.05)	-0.07	(0.45)
Process Improvement	-0.15	(0.06)	-0.49	(0.25)	-0.07	(0.07)	-0.45	(0.45)
Computer Literacy	-0.31	(0.09)	-0.49	(0.65)	-0.30	(0.08)	-1.26	(1.14)
Operations Management	-0.09	(0.04)	-0.50	(0.34)	-0.04	(0.05)	0.12	(0.45)
Microsoft Powerpoint	-0.56	(0.1)	-0.54	(0.44)	-0.51	(0.11)	-0.75	(0.68)
Leadership	-0.16	(0.09)	-0.57	(0.46)	-0.06	(0.09)	-0.48	(0.68)
Marketing	-0.04	(0.05)	-0.60	(0.2)	0.07	(0.06)	-0.56	(0.32)
Performance Appraisals	-0.22	(0.05)	-0.62	(0.34)	-0.06	(0.05)	0.38	(0.48)
SAP	-0.27	(0.05)	-0.64	(0.28)	-0.17	(0.06)	-0.58	(0.4)
Accounting	-0.21	(0.06)	-0.70	(0.33)	-0.15	(0.07)	-0.28	(0.58)
Conflict Management	-0.13	(0.05)	-0.72	(0.24)	-0.00	(0.05)	-0.37	(0.34)
Negotiation Skills	-0.16	(0.05)	-0.72	(0.22)	-0.12	(0.06)	0.13	(0.33)
Microsoft Excel	-0.81	(0.13)	-0.73	(0.65)	-0.73	(0.14)	-1.48	(1.01)
Business Planning	-0.31	(0.07)	-0.76	(0.33)	-0.20	(0.07)	-0.52	(0.54)
Strategic Planning	-0.11	(0.06)	-0.79	(0.25)	-0.05	(0.06)	-0.22	(0.37)
Writing	-0.09	(0.1)	-0.80	(0.58)	0.10	(0.11)	-0.07	(0.78)
Project Management	-0.52	(0.12)	-0.83	(0.51)	-0.31	(0.13)	-2.26	(0.86)
Meeting Deadlines	-0.16	(0.06)	-0.83	(0.34)	-0.14	(0.07)	-0.74	(0.47)
Performance Management	-0.18	(0.07)	-0.84	(0.3)	-0.10	(0.06)	-0.20	(0.47)
Business Development	-0.11	(0.09)	-0.88	(0.42)	-0.04	(0.09)	-0.85	(0.71)
Planning	-0.51	(0.12)	-0.93	(0.65)	-0.40	(0.14)	-0.17	(1.02)
Written Communication	-0.20	(0.11)	-0.95	(0.64)	-0.21	(0.12)	-0.33	(0.98)

	2011-2022				2016-2022			
	OLS		IV		OLS		IV	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Staff Management	-0.30	(0.07)	-1.11	(0.45)	-0.18	(0.06)	-0.75	(0.67)
Microsoft Word	-0.48	(0.08)	-1.27	(0.48)	-0.34	(0.08)	-1.08	(0.64)
Multi-Tasking	-0.28	(0.09)	-1.28	(0.45)	-0.15	(0.09)	-1.18	(0.72)
Customer Service	-0.46	(0.1)	-1.46	(0.59)	-0.37	(0.1)	-1.72	(0.94)
Customer Contact	-0.29	(0.08)	-1.47	(0.55)	-0.13	(0.07)	-2.17	(0.79)
Microsoft Office	-0.88	(0.11)	-1.61	(0.66)	-0.74	(0.13)	-2.31	(1.14)
Building Effective Relationships	-0.60	(0.11)	-1.69	(0.64)	-0.37	(0.12)	-0.44	(1.06)
Physical Abilities	-0.62	(0.11)	-1.71	(0.84)	-0.44	(0.12)	-0.90	(1.47)
Budgeting	-0.71	(0.14)	-1.75	(0.72)	-0.36	(0.14)	-1.26	(1.03)
Scheduling	-0.71	(0.11)	-2.67	(0.68)	-0.43	(0.12)	-0.74	(0.94)