AI Adoption and the Demand for Managerial Expertise*

Liudmila Alekseeva, José Azar, Mireia Giné, Sampsa Samila

31 July 2025

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 growth-oriented and interpersonal skills, such as sales management, listening, teamwork, and creativity, while reducing the need for routine administrative skills, such as budgeting and customer service. 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, organizational change

*Alekseeva: liudmila.alekseeva@kuleuven.be, KU Leuven; Azar: jazar@iese,edu, University of Navarra and IESE Business School; Gine: mgine@iese.edu, IESE Business School and WRDS, University of Pennsylvania; Samila: ssamila@iese.edu, IESE Business School.

We acknowledge the support and funding received from Social Trends Institute STI, 2022. Sampsa Samila acknowledges support from the Spanish Agencia Estatal de Investigación (PID2020-118807RB-I00). We thank Jan Eeckhout, Vicente Cuñat, Fabrizio Ferraro, Stefano Sachetto, Maria Guadalupe, Giovanni Valentini, Carlos Serrano, Dimo Ringov, Juanita Gonzalez-Uribe, Thomas Klueter, and participants at EARIE, DRUID, SMS, AoM, Munich Summer Institute, The Impact of AI on White Collar Work (at Orebro University), IESE AI Conference, IESE Business School Seminar, TUM Seminar, ZEW Conference on Economics of ICT for valuable comments. We are also grateful to Burning Glass Technologies (now Lightcast) for providing the data.

1 INTRODUCTION

How firms organize to create and capture value from new technologies is a foundational question in strategic management For instance, prior waves of information and communication technologies (ICTs) reshaped decision architectures and hierarchies, demonstrating how the organization of knowledge maps to the organization of authority (Bloom, Garicano, Sadun, & Van Reenen, 2014; Garicano, 2000; Rajan & Wulf, 2006). Today, artificial intelligence (AI) presents a profound inflection point, raising critical questions about how firms must reconfigure themselves to organize for innovation, strategize in data-rich environments, and compete. As a general-purpose technology (GPT) AI challenges fundamental assumptions about firm boundaries, organizational design, and, crucially, the nature and future of managerial work itself (Furman & Seamans, 2019; Iansiti & Lakhani, 2020). Yet AI's organizational consequences, particularly for the role and prevalence of managers, remain intensely debated (Csaszar, Ketkar, & Kim, 2024; Lei & Kim, 2024). As rapidly growing firm-level investments in AI are associated with increases in scale and innovation (Babina, Fedyk, He, & Hodson, 2024), getting the organization right is increasingly consequential.

The core of the debate lies in AI's dual potential to either automate existing work or augment human capabilities, a tension central to recent scholarship on technology and work This duality creates conflicting predictions about AI's impact on a firm's organizational capital. On one hand, AI can automate routine managerial tasks such as monitoring, scheduling, and resource allocation, suggesting a path toward substitution (Kellogg, Valentine, & Christin, 2020). This perspective implies that AI could erode the basis of traditional managerial roles by replacing labor in certain tasks particularly those with high average exposure to the technology (Felten, Raj, & Seamans, 2021; Hampole, Papanikolaou, Schmidt, & Seegmiller, 2025). Evidence from industrial robots aligns with this logic, where automation has been linked to declines in managerial headcount, raising the possibility of similar pressures from cognitive AI (Dixon, Hong, & Wu, 2021).

On the other hand, AI may complement managerial work by not only augmenting existing tasks but also creating entirely new managerial roles and responsibilities, making human oversight more strategically vital than ever. The integration of complex AI systems points to the need for new managerial functions to guide implementation, to govern human–AI collaboration, and to ensure alignment with strategic objectives (Hasan, Oettl, & Samila, 2025; Hillebrand, Raisch, & Schad, 2025). Indeed, capturing value from this technology requires investment in complementary organizational assets and capabilities, including managerial capabilities to guide strategy and implementation (Berg, Raj, & Seamans, 2023; Csaszar et al., 2024). Furthermore, by spurring product innovation and enabling firms to manage greater operational complexity and growth, AI may increase the strategic imperative for managers who can coordinate synergistic activities (Dessein, Garicano, & Gertner, 2010). This augmentation perspective suggests a symbiotic relationship where AI adoption makes certain traditional skills obsolete while creating new, valuable human capabilities at the human-machine interface Recent firm-level studies in knowledge-intensive sectors like auditing find that AI adoption is linked to a net increase in professional jobs, not a decrease (Law & Shen, 2024).

To date, the net effect of these competing pressures remains a conceptual debate largely unaddressed by large-scale empirical evidence at the firm level. A persistent bottleneck in studying AI's organizational effects is the lack of firm-level data and recent systematic reviews document a continued shortage of large-sample, organizationally grounded studies While occupation-level studies have identified managers as highly exposed to AI (Felten et al., 2021; Lane, 2024; Tolan et al., 2021; Webb, 2019), this tells us little about how firms are actually redesigning their organizational structures in response to AI adoption. Do firms that invest in AI ultimately employ more or fewer managers? And how does the nature of the managerial role change?

This paper examines the organizational impact of AI adoption, focusing on the role of managers and their required skill set. We construct a large U.S. firm–year panel (2010–2022)

that allows us to measure firm-level AI adoption and managerial demand while applying a quasi-experimental research design to identify the causal impact of AI. We link Lightcast's universe of online job postings with Compustat financial data. We measure a firm's AI adoption (*AI Share*) as the proportion of its annual job postings that are AI-related, identified through a data-driven skill co-occurrence method (e.g., Babina et al., 2024) that links postings to core AI skills such as machine learning. We measure managerial intensity as the share of postings in managerial occupations (*Managers Share*), based on 2-digit SOC code 11, and also track the number of managerial vacancies. Because job postings capture the demand for skills regardless of whether positions are ultimately filled, they provide a timely indicator of how firms seek to redesign their organizations in response to AI.

Because AI adoption is endogenous (as firms anticipating growth may both hire more managers and invest in AI), we use a shift-share instrumental variable design (Adao, Kolesár, & Morales, 2019; Bartik, 1991; Borusyak, Hull, & Jaravel, 2022, 2025; Goldsmith-Pinkham, Sorkin, & Swift, 2018) to isolate the causal effect. The instrument interacts a firm's historical (2010) occupational mix (the "share") with the subsequent national growth in AI hiring within each occupation (the "shift"). The underlying instrument's logic is that a firm's historical workforce predisposes it to future AI adoption. Therefore, firms that employed more workers in occupations where AI hiring later grew nationally are predicted to experience a larger AI adoption shock.

Instrumented estimates indicate that AI adoption increases managerial intensity. A one-percentage-point rise in *AI Share* leads to a roughly 1.2 percentage-point increase in *Managers Share* and raises the number of managerial vacancies by about nine percent. Crucially, this effect is not uniform; as shown in our heterogeneity analysis, it is driven almost entirely by firms with high technological capabilities and strong innovation orientations, specifically those with significant R&D expenditures and a high intensity of software-related skills. This finding stands in contrast to the modest downward drift in *Managers Share* observed in the raw data over the sample period, underscoring that marginal AI adoption is manage-

rially complementary even amid declining aggregate trends. This result suggests that the strategic benefits of AI are realized not by simply substituting labor, but by investing in complementary managerial capital supporting and directing the new technology.

Furthermore, we find a significant evolution in the skills required of managers. As firms adopt AI, they increasingly seek managers with growth-oriented and interpersonal skills, such as Sales Management, Listening, and, in certain settings, Creativity and Teamwork, while demand for routine administrative skills, such as Budgeting, Customer Service, and proficiency in office software, declines. This shift suggests a fundamental reorganization of work: as AI automates predictable tasks, managers are redeployed to strategize, handle exceptions, coordinate complex workflows, and foster creative problem-solving that falls outside the scope of algorithms. This pattern aligns with theories predicting that as AI handles analytical work, the value of uniquely human capabilities, such as social and emotional intelligence, will rise (Deming, 2017; Huang, Rust, & Maksimovic, 2019).

This paper makes two contributions to strategy research on technology–organization coevolution. First, we provide large-sample, firm-level evidence that AI adoption is associated with higher managerial intensity, highlighting the importance of complementary managerial capital in realizing the returns to AI. We sharpen this contribution by showing that this complementarity is strongest in innovative and technologically advanced firms. Second, we show that AI adoption alters the skill content of managerial demand, shifting value away from routine administrative tasks toward growth-oriented and interpersonal capabilities that enable firms to scale complex, AI-enabled operations. Together, these findings qualify analogies to prior automation waves and offer guidance to leaders designing organizations for the age of intelligent machines.

2 AI AND THE RECONFIGURATION OF MANAGERIAL WORK

The diffusion of AI presents a fundamental challenge to our understanding of firm structure and the role of management. To develop a testable theory of AI's organizational impact, we ground our arguments in foundational concepts from strategy and organization theory: complementarities within an activity system (Milgrom & Roberts, 1990; Porter, 1996); knowledge hierarchies that structure authority (Garicano, 2000; Grant, 1996); coordination for synergies across interdependent units (Dessein et al., 2010; Thompson, 1967); and dynamic capabilities that enable firms to reconfigure resources in response to technological shifts (Teece, Pisano, & Shuen, 1997). Building on these anchors, we frame AI's impact as the net outcome of two competing forces: AI-enabled *informational control*, which facilitates managerial contraction, and AI-driven *strategic reconfiguration*, that can compel managerial expansion.

These forces operate at the task level but aggregate at the role level. We distinguish between discrete managerial *tasks* (e.g., performance monitoring) and formal managerial *roles*, which bundle tasks with accountability and decision rights. Following the economics of automation, AI adoption generates both a displacement effect on existing tasks and a reinstatement effect via the creation of new, human-led activities (Acemoglu, Autor, Hazell, & Restrepo, 2022; Acemoglu & Restrepo, 2018). The net effect on management is a micro-to-macro aggregation problem: the reallocation of tasks within units scales up to changes in the firm's demand for managerial roles, altering both the mix of role types and, where new interfaces emerge, the number of roles (Garicano, 2000). Our use of job postings provides a direct, role-level measure of intended demand, capturing both the number of positions and their required skill content (coded using Lightcast's skill classification), even if internal reallocations are not directly observable.

2.1 Mechanisms of Managerial Contraction: AI-Enabled Informational Control

The first force, AI-enabled informational control, enhances a firm's ability to direct work with less human supervision, displacing traditional managerial tasks. AI-powered platforms can automate codifiable supervisory routines like performance monitoring and scheduling, substituting for work historically done by first-line supervisors (Kellogg et al., 2020). Simultaneously, AI-enhanced dashboards can centralize decision-making by providing senior leaders with real-time, granular data, reducing the need for intermediate managers who traditionally aggregate information (Bloom et al., 2014). This enhanced visibility can catalyze deliberate corporate "flattening", as firms eliminate management layers and widen spans of control, a dynamic documented in prior IT waves (Pinsonneault & Kraemer, 1997; Rajan & Wulf, 2006). While human oversight is rarely eliminated entirely, these contraction mechanisms collectively suggest that AI adoption will be associated with a decline in firm demand for managers with routine administrative skills.

2.2 Mechanisms of Managerial Expansion: AI-Driven Strategic Reconfiguration

Countervailing the contractionary forces are reinstatement channels tied to AI-enabled strategic reconfiguration. We expect these expansionary forces to dominate at the firm level, especially in innovative, software-intensive, and data-rich firms, by creating new strategic imperatives that require more, and differently skilled, managers (Brynjolfsson, Hitt, & Yang, 2002; Milgrom & Roberts, 1990; Teece et al., 1997).

First, AI-driven productivity gains enable firm scaling and diversification. As firms expand into new product lines or geographies, they require more accountable leaders to manage the increased coordination complexity of these new units, even if the manager-per-employee ratio within a unit declines (Babina et al., 2024). Scope expansion raises coordination com-

plexity non-linearly, increasing demand for managers who can organize for synergies across interdependent units (Dessein et al., 2010). Consistent with the logic of complementarities, realizing value from technology requires complementary investments in organizational capital, especially in management (Brynjolfsson et al., 2002; Milgrom & Roberts, 1990).

Second, AI may drive a recomposition of teams by augmenting subordinate performance. Evidence from studies on non-managerial positions shows a significant boost in productivity when workers are supported by AI tools (Jia, Luo, Fang, & Liao, 2024; Shanthikumar & Yoo, 2024). This presents a strategic choice: firms can either maintain output with fewer employees or redeploy the newly freed-up capacity toward new projects and product lines. In a growth context, the latter is more likely. Thus, even if span of control falls within a unit, the firm can run more parallel, manager-led units, raising both the count and share of managerial roles at the firm level.

Third, the integration of complex AI systems introduces significant new challenges in governance, risk, and compliance. The need to manage model risk, ensure ethical use, build organizational trust in algorithmic systems (Vanneste & Puranam, in press), and comply with emerging regulations, such as those outlined in the NIST AI Risk Management Framework, necessitates dedicated managerial roles and new oversight functions (Berg et al., 2023; National Institute of Standards and Technology, 2023). This creates demand for managers that is not directly tied to production headcount, but rather to the complexity and risk profile of the technology itself. Hence, managerial demand scales with the organization's AI complexity and risk surface.

Fourth, effective AI implementation requires human–AI orchestration and translation (Choudhary, Marchetti, Shrestha, & Puranam, 2025). As AI automates routine analytics, competitive advantage increasingly relies on human creativity and collaboration (Krakowski, Luger, & Raisch, 2023). This creates a premium for managers who can lead human–AI ensembles, navigate the new terrain of algorithmic work, and translate AI insights into strategic action (Hillebrand et al., 2025; Huang et al., 2019; Jia et al., 2024). These roles also

involve (re)allocating decision authority between humans and algorithms, as well as managing trust and perceived agency (Kim, Glaeser, Hillis, Kominers, & Luca, 2024; Vanneste & Puranam, in press). Moreover, AI can widen the firm's search scope beyond its established knowledge base by lowering the costs of engaging external communities and crowd platforms, an instance of that increases the need for managerial orchestration across boundaries (Afuah & Tucci, 2012). Evidence from professional services already shows that AI adoption can expand, not shrink, professional staffing to handle these new oversight and orchestration demands (Law & Shen, 2024).

Together, these mechanisms predict that higher AI adoption is associated with (i) greater managerial intensity (measured by both the share of managerial roles and, in scaling contexts, their absolute counts), and (ii) a shift in the skill mix of managerial postings toward growth and coordination (e.g., product/program management, strategy, cross-functional leadership), governance and risk (e.g., model risk, compliance), and human-centric capabilities (e.g., team leadership, stakeholder management), accompanied by relative declines in routine administrative skills.

2.3 The Contingent Role of Firm Capabilities and Context

The balance between managerial contraction and expansion is not uniform, but contingent on a firm's strategic orientation and operating context. We argue that whether AI-enabled *informational control* (contracting) or AI-driven *strategic reconfiguration* (expanding) dominates depends on a firm's *dynamic capabilities*—its ability to sense opportunities, experiment, and reconfigure in response to technological change (Teece et al., 1997). In strategy terms, stronger capabilities are typically coupled with tighter complementarities and richer organizational capital, enabling firms to convert AI-enabled productivity gains into scope expansion and the creation of new interfaces that require accountable leadership (Brynjolfsson et al., 2002; Milgrom & Roberts, 1990).

We operationalize two firm-level capabilities that signal this orientation. First, an *in-*

novation orientation, proxied by R&D intensity, reflects a commitment to exploring new products and services; in such firms, AI is more likely to be deployed for growth and recombination rather than pure process optimization, thereby generating new manager-led initiatives (Bardhan, Krishnan, & Lin, 2013). Second, *technological expertise*, proxied by software-skill intensity, supplies the complementary human capital needed to integrate, extend, and scale complex AI systems, shifting coordination demands upward and outward (Bresnahan, Brynjolfsson, & Hitt, 2002). In capability-constrained firms, by contrast, AI is more likely to be applied to standardization and cost-cutting, a context in which contractionary informational-control effects can dominate.

Beyond capabilities, structural characteristics of the work system condition how AI affects managerial demand. Where core workflows are interdependent and tightly coupled across units, AI adoption tends to surface more cross-unit interfaces—for example, between engineering, operations, quality, and suppliers—that require orchestration and exception-handling. In such settings, coordination problems are less decomposable, and the premium on accountable leadership rises (Dessein et al., 2010; Thompson, 1967). By contrast, where tasks are highly codifiable and modular, AI-enabled observability and decision support can substitute for intermediate aggregation and facilitate the recentralization of decision rights into analytics platforms and control functions (Bloom et al., 2014; Kim et al., 2024). In those contexts, we expect more pronounced *role recomposition* toward oversight and translation even when overall managerial intensity changes only modestly.

A further contingency arises when AI is embedded in physical assets and processes. When algorithmic systems interact with tangible production technologies—as in predictive maintenance, line reconfiguration, or supply synchronization—changes propagate through material constraints that are costly to reverse. This deep physical–digital embedding increases boundary-spanning coordination needs and elevates program leadership, potentially raising the number of accountable roles even if spans of control within units widen (Zammuto & O'Connor, 1992). Orthogonal to these production considerations, the governance, risk,

and compliance (GRC) surface of AI—encompassing model risk, safety, auditability, and regulatory exposure—creates demand for managerial oversight and stakeholder management independent of headcount in production units (National Institute of Standards and Technology, 2023). As the organizational risk surface expands, we therefore expect the composition of managerial roles to tilt toward governance and assurance responsibilities.

Taken together, these contingencies imply distinct predictions for both *managerial intensity* and *managerial composition*. Intensity should rise when AI adoption coincides with high interdependence and tight coupling, substantial physical embedding, and capabilities sufficient to convert productivity gains into scope expansion (e.g., additional product lines or geographies that create new interfaces). Intensity effects should be weaker when work is highly codifiable and modular and when firms primarily leverage AI for standardization and recentralization. Composition should shift even when intensity does not: as algorithms absorb routine analytics and monitoring, managerial roles move toward growth coordination, cross-functional leadership, stakeholder management under uncertainty, and the governance of human–AI collaboration (Hillebrand et al., 2025).

Although our theory is stated over general design constructs, these features are imperfectly reflected in industry classifications. We therefore use sectors as coarse proxies to organize our heterogeneity tests. Manufacturing, for instance, serves as a canonical instance of high interdependence and physical embedding, where AI adoption across tightly coupled systems elevates boundary-spanning coordination and accountable leadership (Thompson, 1967; Zammuto & O'Connor, 1992). By contrast, finance and other analytics-intensive services often exemplify high codifiability and strong control functions; here, AI-enabled observability can facilitate the recentralization of decision rights, shifting managerial composition toward oversight with more muted changes in intensity (Bloom et al., 2014; Kim et al., 2024; National Institute of Standards and Technology, 2023). Trade sectors (wholesale/retail) combine standardized internal routines with extensive boundary coordination; whether AI yields expansion through reconfiguration or mainly standardization depends on

firm capabilities and the extent to which boundary interfaces are transformed rather than only internal processes. Empirically, we therefore report sector-level patterns as illustrations of these pathways and supplement them with firm-level proxies (e.g., R&D intensity and software-skill intensity) that map more directly to our theoretical constructs.

3 DATA

3.1 Vacancy-based Measures

Estimating firm-level AI adoption has been a major challenge for researchers. Given the lack of large-scale datasets on AI technology adoption, it is often impossible to determine whether, and to what extent, firms are using AI. However, to proxy for AI adoption, we leverage the insight that AI technologies, unlike some other technology types, require highly specialized human capital.[1] Accordingly, this paper adopts a skill-based measure of AI adoption, using data on job postings from Lightcast (formerly Burning Glass Technologies).

Lightcast is one of the leading providers of labor market data, and its job postings database has been widely used in research on labor markets and technology adoption (e.g., Alekseeva, Azar, Giné, Samila, & Taska, 2021; Babina et al., 2024; Goldfarb, Taska, & Teodoridis, 2023; Gulati, Marchetti, & Puranam, 2023). Our version of the dataset contains information on nearly 388 million U.S. vacancies posted in 2007 and from 2010 to 2022, offering highly detailed descriptions of job attributes. Specifically, each posting includes the employer's name and industry, job title, location, and offered wage, as well as candidate requirements such as education, experience, and, crucially, a list of required skills.[2] This level of detail is a key strength of the Lightcast data, enabling job-, occupation-, and firm-level analyses of skill demand. These features also make it one of the few data sources that

[1] For instance, Tambe (2014) discusses the importance of highly skilled labor in extracting value from big data technologies. The number of IT workers as a measure of firms' IT investments has been widely used in the literature (e.g., Tambe & Hitt, 2012; Tambe, Hitt, & Brynjolfsson, 2012; Tambe, Hitt, Rock, & Brynjolfsson, 2019). Building on this literature, we argue that firms' demand for AI-related skills can serve as a proxy for their level of AI adoption.

[2] Lightcast uses an advanced algorithm to extract and classify individual skills into standardized categories and clusters.

allow researchers to track demand for AI-related skills and to proxy firm-level AI adoption.

We use a data-driven approach to identify AI-related vacancies.[3] The intuition behind this approach is to estimate how closely a job vacancy is associated with AI-related tasks by exploring the data rather than defining AI-related skills ex ante. Specifically, we assess how often each skill in the data co-occurs with unambiguous AI-related skills to determine its degree of AI-relatedness. Vacancies listing more such skills are thus more likely to be AI-related. This probabilistic method is commonly used when direct measures are unavailable and was first applied to AI-related vacancies by Babina et al. (2024).[4]

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:

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

Panel A of Figure 1 presents the evolution of this measure of AI adoption over time. The average share of jobs requiring AI skills increased more than tenfold between 2007 and 2022, rising from below 0.1 percent to 1.0 percent of firms' vacancies. We also observe that growth in the *AI Share* was slow between 2007 and 2010, began to accelerate in 2012, and picked up further after 2016.

[Insert Figure 1 Here]

In our robustness tests, we also use a continuous measure of AI adoption (*Continuous AI Share*), defined as the average vacancy-level AI-relatedness at the firm-year level. Additionally, we test the robustness of our results by replacing the main *AI Share* measure

[3] Although it would be interesting to explore more granular measures that separate different types of AI, our data is not detailed enough to pick up the exact technology or application of AI that a firm is hiring for in most cases. For this reason, we focus on a broad measure of demand for AI.

[4] We follow their approach in several steps. First, we identify vacancies mentioning "Machine Learning," "Natural Language Processing," "Computer Vision," or "Artificial Intelligence" (or their abbreviations) in job titles or skills. Second, for each skill in the data, we compute the proportion of its occurrences in these AI-flagged vacancies relative to its total occurrences, generating a measure of AI-relatedness. Third, for each posting, we calculate the average AI-relatedness across all listed skills (excluding skills appearing in fewer than 20 postings). Finally, we classify a vacancy as AI-related if this average exceeds 10%. This threshold, though somewhat arbitrary, follows Babina et al. (2024), who found it effectively captures relevant AI skills.

with an alternative based on AI-related keywords (e.g., Alekseeva et al., 2021; Goldfarb et al., 2023), as listed in Online Appendix Table A1.[5] Online Appendix Figure A1 shows that both the main *AI Share* measure and the keyword-based measure follow similar trends, with the latter generally higher. This suggests that the two measures are consistent, though the keyword-based approach captures additional AI-related vacancies. Accordingly, *AI Share* based on jobs' AI-relatedness score can be viewed as a more conservative measure of AI adoption.

For our analysis, we also calculate the intensity of demand for managers, denoted as *Managers Share*. To compute this measure we divide the number of vacancies in management occupations (2-digit SOC code 11) within the firm by the total number of the firm's vacancies. The demand for managers in firm i and time t is calculated as follows:

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

In contrast to the clear upward trend in *AI Share*, the share of managerial vacancies declined from around 19 percent in 2007 to approximately 16 percent by 2022, as shown in Panel B of Figure 1. This contrasts with the slowly increasing total number of managerial vacancies posted by firms. Thus, while the absolute demand for managers has grown, the demand for non-managerial jobs appears to have grown at a faster pace, reducing the relative share of managerial vacancies. Online Appendix Figure A2 shows that this decline is primarily driven by companies with lower growth in AI adoption. The next section examines more closely whether the trends in *AI Share* and *Managers Share* are related, using a regression framework.

Finally, to estimate the intensity of demand for a specific skill in managerial jobs, we divide the number of a firm's managerial vacancies requiring that skill by the total number

[5]While the bag-of-words method has limitations, it is transparent and can better capture AI jobs that include many non-AI-related skills, which may lower the AI-relatedness score, particularly in non-IT roles. Goldfarb et al. (2023) also suggest that this method helps identify early technology diffusion, as firms often specify required technology skills in job postings.

of the firm's managerial vacancies. We focus on the 100 most prevalent skills required in managerial vacancies across companies in our final sample.[6] Accordingly, the demand for a specific skill within managerial vacancies in firm i at time t is calculated using the following ratio:

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

We acknowledge a limitation in using job postings data as a proxy for actual employment. Posted positions are not always filled, and the job description may not match the profile of the employee ultimately hired. Despite these concerns, recent research provides evidence supporting the validity of job postings data as a proxy for firm-level investment in AI expertise. A study by Babina et al. (2024) examines the similarity between AI-related vacancies in Lightcast and the actual employment of AI-skilled workers, based on resume data from Cognism. The authors find that vacancy- and resume-based measures of AI hiring intensity are strongly correlated and generate similar results in the analysis of AI's impact on firm performance.[7] Nevertheless, our results on changes in managerial intensity should be interpreted as suggestive of shifts in the managerial span of control, rather than as a direct measure.

Importantly, a large part of our analysis focuses on understanding changes in the demanded profile of managers. For this purpose, job postings offer key advantages over employment data, as they more precisely capture evolving skill requirements. Overall, the detailed information in job descriptions, the timeliness of job postings, and their consistency with broader labor data make Lightcast a unique source of information which allows us to trace the demand for AI and managerial talent across firms and in various occupations within

[6] Lightcast vacancy data includes more than 16,000 unique skills, making it computationally challenging to analyze all of them.

[7] Additional validation of job postings data is provided by Carnevale, Jayasundera, and Repnikov (2014) and Hershbein and Kahn (2018), who show that Lightcast ("Burning Glass" in those studies) job postings correlate strongly with job openings in the JOLTS data. They also show that aggregate and industry trends in Lightcast data align closely with other sources of job vacancies data, such as CPS, OES, and JOLTS.

firms.

3.2 Sample

Our Lightcast data consists of all online job postings in the U.S. during 2007 and from January 2010 until December 2022, which encompasses a total of approximately 388 million vacancies. After dropping vacancies that do not have employer name and represent internships, we still have the sample of 277 million vacancies that we match to Compustat dataset. We focus on the Compustat-matched sample to be able to classify companies reliably into industry sectors, filter out non-commercial organizations, such as government agencies, universities, and non-profit companies, and control for company financial characteristics.[8] Out of all Compustat matches, we keep a balanced panel of firms that matched with the vacancy data in 2010–2022, have at least 50 vacancies per year and all required Compustat characteristics in 2011–2022, but we exclude firms that produce AI or help implement AI solutions for other companies (2-digit NAICS equal 51 and 54). For this sample of companies, when available, we add the vacancy data in 2007 to construct the descriptive graphs and conduct pre-trend analysis over 2007–2010 period, while the key regressions at the firm-year level cover 2011–2022. The resulting sample used in the regressions includes 823 unique companies and 9,876 observations at the company-year level. These firms, in total, posted 51 million vacancies.

Table 1 provides summary statistics for AI-related and managerial vacancies in the sample. On average, 0.5 percent of company vacancies are AI-related, as measured by *AI Share*. The table also indicates that 16.1 percent of company vacancies represent managerial positions. Additionally, the table provides an overview of the skills required in managerial vacancies. Communication skills are the most frequently demanded, appearing in nearly

[8]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, 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, Dorn, Hanson, Pisano, and Shu (2020). This algorithm matches firms not only on their names, 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 and when databases use abbreviations or short versions of company names.

49 percent of managerial vacancies, followed by Budgeting (29.4%), Planning (27.8%), and Teamwork / Collaboration (26.2%). The table also highlights the prevalence of more technical skills, such as Project Management (23.0%) and Scheduling (18.6%). Thus, the table reflects the multifaceted nature of managerial roles in organizations, where both soft skills and technical competencies are in high demand. Descriptive statistics for the full list of the top 100 managerial skills most frequently required by firms in our sample can be found in Online Appendix Table A2, which also includes less common managerial skills, such as Risk Management (3%), Thought Leadership (2%), and Data Analysis (2%). Additional firm characteristics and control variables are summarized in Online Appendix Table A3.

[Insert Table 1 Here]

Table A4 tracks changes in key vacancy characteristics and managerial skill requirements over 2011–2016 and 2016–2022 periods. Consistent with earlier figures, the table shows a substantial increase in AI-related job postings and a decline in the share of managerial vacancies over the observation period. Notably, the change in the demand for the top ten managerial skills listed in the table is positive and especially strong in the earlier time period. While not shown in the table, a similar positive trend is observed for most of the remaining top 100 skills that we study. Overall, this suggests that, unconditionally, the demand for the majority of key managerial skills has been rising over time.

4 EMPIRICAL METHODOLOGY

4.1 AI Adoption and the Demand for Managers

To study the effect of AI adoption by firms on the demand for managers, we estimate the following regression specification. As we are interested in within-firm changes, we include firm fixed effects in all main specifications:

$$\text{Managers Share}_{i,t} = \beta \text{AI Share}_{i,t} + \gamma X_{i,t} + \delta_i + \theta_{s,t} + \varepsilon_{i,t}. \quad (1)$$

Managers Share$_{i,t}$ is the share of managerial vacancies in a firm, *AI Share*$_{i,t}$ is the main variable of interest estimated as described in section 3.1 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*), $X_{i,t}$ is a vector of controls for company characteristics, and δ_i and $\theta_{s,t}$ are firm and 2-digit NAICS industry-year fixed effects. All main tables report results after controlling for the natural logarithm of total firm's vacancies that adjusts for the fluctuations in the firm's total labor demand. In additional tests, we also present results without controlling for the firm's overall hiring level and with the inclusion of various additional control variables, to demonstrate the consistency of our findings and ensure transparency in their interpretation.

4.2 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:

$$\text{Managerial Skill } j \text{ Share}_{i,t} = \beta_1 \text{AI Share}_{i,t} + \gamma X_{i,t} + \delta_i + \theta_{s,t} + \varepsilon_{i,t}. \tag{2}$$

Managerial Skill Share$_{i,t}$ is the share of managerial vacancies requiring one of the top-100 managerial skills in a firm, *AI Share*$_{i,t}$ is the main variable of interest estimated as described in section 3.1 and multiplied by a 100, $X_{i,t}$ is a vector of controls as described above, and δ_i and $\theta_{s,t}$ are firm and industry-year fixed effects.

4.3 Identification Strategy for AI Adoption

4.3.1 Instrument estimation

The main endogeneity concern in estimating the causal effect of AI adoption on firm's managerial intensity and the demand for managerial skills is potential omitted variable bias. We include firm fixed effects to control for time-invariant omitted firm characteristics and industry-specific time fixed effects in all main specifications. However, we cannot fully ad-

dress endogeneity due to omitting important time-varying firm-level characteristics, such as within-firm processes transformation, changes in organizational structure, or changing management quality, which could be correlated with both AI adoption and managerial structure. Another concern is measurement error: *AI Share* may be a noisy measure of AI adoption, because firms can post more AI-related vacancies than needed or, on the contrary, they might look for AI specialists via alternative ways (e.g., acquihires or internal training) and limit AI-related job postings while still adopting AI.[9]

To address these endogeneity concerns, we employ a shift-share instrumental variable. The instrument leverages the insight that certain occupations are more predisposed to adopt AI based on their task content (e.g., Brynjolfsson, Mitchell, & Rock, 2018; Felten et al., 2021; Tolan et al., 2021). Therefore, we expect that firms with higher shares of AI-exposed occupations in the period before the growth of AI adoption are more likely to adopt AI as the technology becomes more widespread. Specifically, the instrument is constructed by interacting a firm's pre-period (2010) occupational shares at the 5-digit SOC level with national occupation-level *AI Shares* over time. We keep the occupation shares fixed in 2010 to ensure that the instrument captures predetermined exposure to AI and to avoid bias stemming from firms adjusting their workforce structure in response to the technological opportunities. Formally, the exposure to AI of firm i in time t is given by:

$$B_{i,t} = \sum_{o=1}^{O} s_{i,o,2010} \times \text{AI Share}_{o,t}, \tag{3}$$

where $s_{i,o,2010}$ is the share of occupation o in firm i in 2010, and $AI\ Share_{o,t}$ is the national AI adoption rate in occupation o at time t.

This instrumental variable leverages identification from many plausibly exogenous shifts in AI adoption at the occupation level (Borusyak et al., 2025).[10] Three considerations sup-

[9]Other concerns include simultaneity (i.e., AI adoption and changes in managerial structure might simply follow similar trends) or reverse causality (e.g., firms with a high managerial intensity may adopt AI to optimize management tasks). While theoretically relevant, we consider these issues to be less central.

[10]This approach relies on two key assumptions: 1) conditional quasi-random shock assignment, and 2) the presence of many uncorrelated shocks, shock clusters, or many weakly correlated shocks. This IV approach

port the plausibility of treating nationwide occupation-level AI adoption rates as exogenous to the firm-level outcomes we study. First, national AI adoption trends are largely driven by technological feasibility rather than firm-specific shocks. This is particularly likely given that we use all U.S. firms in the Lightcast data to estimate nationwide adoption rates. Second, individual firms in our data are too small to influence national AI adoption rates, reducing the risk of mechanical correlation between the instrument and the regression residuals, which can arise when the focal firm is included in the shifts estimation. Finally, the occupational shares used to construct the instrument are measured prior to the AI adoption wave. This helps to ensure that the growth of AI adoption does not affect the occupational structure itself. We also exclude IT and Professional Services firms from our analysis, as they may have had early insights into AI opportunities and could have preemptively adjusted their workforce composition.

However, the assumption that shocks (i.e., AI adoption rates across occupations) are as good as randomly assigned may not hold unconditionally in our setting. In reality, certain occupations (e.g., Computer and Mathematical) are more likely to experience faster growth in AI adoption than others (e.g., Legal or Science) due to their task content and technological complementarity with AI. This creates a potential identification threat if firms with high shares of such occupations also differ systematically in their managerial trends for reasons unrelated to AI. For instance, these firms may adopt other technologies (e.g., robots, data analytics tools) that are correlated with future AI exposure and independently influence managerial practices (e.g., Bloom et al., 2014; Dixon et al., 2021).

Nevertheless, we do not expect this to pose a significant concern once we condition on firm-level and shock-level controls. We include firm fixed effects to absorb time-invariant firm characteristics, such as technology use and management quality[11] and control for industry-specific time fixed effects that adjust for varying trends in AI adoption and managerial

remains valid even if occupational shares are endogenous (Borusyak et al., 2025).

[11] Although prior research shows that firms with high AI adoption tend to differ in characteristics such as size and R&D intensity (e.g., Alekseeva et al., 2021; Babina et al., 2024), our empirical strategy focuses on within-firm changes over time, mitigating bias from such differences.

practices across industries in the baseline regressions. In robustness tests, we include controls for exposure to other technologies (i.e., robotics, data analytics, and cloud computing), as well as changes in occupational skill content (e.g., cognitive, social, or software skills), using both direct firm-level measures and shift-share analogs. Most importantly, we test for the presence of pre-trends in our main outcomes and find no evidence that the exclusion restriction is violated.

4.3.2 Instrument validity tests

To provide further evidence on the validity of the key assumptions underlying our IV strategy, this section presents a series of diagnostic tests. Specifically, we evaluate the instrument's relevance and, following the approach proposed by Borusyak et al. (2022), examine the exogeneity assumptions through several steps. First, we analyze the distribution of occupation-level *AI Shares* used as shocks in the instrument construction to evaluate the plausibility of the assumption that many conditionally uncorrelated shocks contribute to the overall variation. Second, we conduct a series of pre-trend tests to check whether firms with higher predicted exposure to AI were already on different trajectories in terms of managerial demand prior to the main period of AI adoption. Third, we run shock-level IV regressions to account for the potential correlation of residuals across firms exposed to similar shocks and therefore correct the standard errors. Finally, we test the sensitivity of our results to the inclusion of alternative sets of firm-level and shock-level controls.

We begin by evaluating the relevance of the instrument. The first-stage regression results indicate that the shift-share instrument is strongly correlated with firm-level AI adoption. The coefficient of the instrument is positive (1.087) and highly statistically significant, with a first-stage F-statistic of 89.8 highly exceeding the conventional threshold of 10. This suggests that the instrument explains a meaningful portion of the variation in firm-level *AI Share*. The magnitude of the coefficient implies that a one-percentage-point increase in predicted AI exposure, as captured by the instrument, is associated with a 1.09-percentage-point increase in a firm's *AI Share*.

Table 1, Panel B, presents descriptive statistics for the shocks and exposure shares used to construct the instrument.[12] The distribution of occupation-level AI adoption rates shows considerable variation: the mean *AI Share* is 0.3 percent with a standard deviation of 2.5 percent. However, since the interquartile range is rather narrow (0.1%), the AI adoption rates appear to be skewed to the right.[13] At the same time, the inverse of Herfindahl-Hirschman Index (HHI) for exposure shares is high (778), with the largest SOC weight equal to 0.5 percent, suggesting substantial variation in occupational exposure across firms and supporting the assumption that the instrument leverages many distinct shocks.

To further validate the exogeneity of the instrument, we conduct a pre-trend analysis using vacancy data available in 2007 and 2010. Table 2 reports the results of this analysis. In Panel A, the dependent variable is the change in *Managers Share* between 2007 and 2010; in Panel B, it is the change in the natural logarithm of managerial vacancies over the same period. We regress these dependent variables on the change in the instrument over the full 2011–2022 period (column (1)) and over two subperiods, 2011–2015 and 2016–2022 (columns (2) and (3)), to check that the pre-trends are absent relative to both slower and faster phases of AI adoption. We also repeat the pre-trend tests after transforming the data to the shock (occupation) level, following the approach in Borusyak et al. (2022) (columns (4) and (5)). In all these tests, we find no statistically significant differences in pre-period growth in either the share or the number of managerial vacancies between firms with higher and lower predicted AI exposure. This suggests that firms more exposed to AI were not already on different trends in terms of the intensity of managerial demand prior to the onset of widespread AI adoption. We present the remaining IV-related validation tests in the section on robustness checks.

[Insert Table 2 Here]

[12] Before generating these statistics, the data were aggregated to the occupation-year level, following Borusyak et al. (2022).

[13] We assess whether this skewness poses a threat to the exogeneity assumption using pre-trend tests and testing the sensitivity of results to the inclusion of shock-level controls in the following tests.

5 RESULTS

5.1 AI Adoption and the Demand for Managers

5.1.1 Baseline results

Table 3 presents regression results showing how AI adoption influences the demand for managers in the analyzed firms. Both OLS and instrumental variable models following specification 1 indicate a positive relationship: firms with higher AI adoption exhibit a greater intensity of demand for managerial roles. This first result suggests that, as AI is getting integrated into business operations, the demand for managers increases. The economic magnitude of the effect of AI adoption on the demand for managers is substantial. The OLS results suggest that when the firm's *AI Share* increases by one percentage point, the firm's *Managers Share* goes up by 0.3 percentage points, or by around two percent relative to the unconditional mean (column (1)), and the number of posted managerial vacancies rises by three percent (column (3)). However, the IV results suggest that the effect size estimated by the OLS regressions may be biased downward, as the coefficients of *AI Share* are larger in both columns (2) and (4). Specifically, the IV regressions indicate that when *AI Share* of the firm increases by one percentage point, *Managers Share* grows by 1.2 percentage points, or by around 7.5 percent (column (2)), and the number of managerial vacancies grows by nine percent (column (4)).[14]

[Insert Table 3 Here]

We conduct additional analyses to check the robustness and dynamics of the relationship between AI adoption and the demand for managers across different time periods and empirical specifications. Table A5 presents regressions for two subperiods: 2011–2015 (slower

[14]The larger coefficients in the IV regressions suggest that the OLS estimates may be biased downward. This can occur if unobserved firm characteristics are positively correlated with AI adoption but negatively correlated with managerial intensity. For example, companies improving their managerial quality and workflows may require fewer managers but also be more likely to adopt AI due to a better understanding of its benefits.

AI adoption) and 2016–2022 (faster AI adoption). The results show that the effect of AI adoption on managerial demand is statistically stronger in the later subperiod, as the standard errors of the instrumented coefficients are smaller. Nevertheless, the coefficients are consistently positive in both subperiods.

Given the concern that the effect of AI adoption on managerial structure may not occur immediately, we repeat the key analysis using long-differences specifications reported in Table A6. The results support our panel regression results, showing that even if changes in managerial structure occur gradually, there is a positive impact of AI on the demand for managers in absolute and relative terms over 2011–2022.

To better understand the drivers of the increase in managerial intensity, we repeat the regressions while progressively tightening the set of controls and fixed effects. We begin with specifications that include only industry-year fixed effects and then sequentially add controls for firm size and firm fixed effects. This analysis is conducted for *Managers Share*, managerial hiring, overall hiring, and non-managerial hiring. The results presented in Table 4 show that the increase in *Managers Share* following AI adoption is partially explained by slower growth in non-managerial hiring, while managerial hiring generally scales with firm growth. Importantly, even after controlling for firm size, firm fixed effects, and overall hiring levels, the relative demand for managers, *Managers Share*, continues to rise, pointing to a shift in organizational structure, rather than a pure increase in managerial hiring in proportion to firm growth .[15] Importantly, even after controlling for firm size, firm fixed effects, and overall hiring levels, the relative demand for managers, *Managers Share*, continues to rise, pointing to a shift in organizational structure, rather than a pure increase in managerial hiring in proportion to firm growth.

[Insert Table 4 Here]

[15]This pattern appears to hold primarily in the earlier part of the sample (2011–2015): as shown in Panel B of Table A8, AI adoption has no negative effect on total and non-managerial hiring in the later period (2016–2022). Thus, during this subperiod, the growth in *Managers Share* is driven by a relatively stronger increase in managerial hiring.

5.1.2 Robustness checks

To further support the reliability of our IV-based inference and strengthen causal interpretation of the relationship between AI adoption and managerial intensity, we conduct an extensive series of robustness checks. These checks are designed to assess whether our results are sensitive to specific choices we made in constructing the instrument and specifying the regressions. A summary of the robustness results is presented in Table 5, which compares the baseline IV estimates in row (1) to those obtained from various modified specifications. For each specification, we report the estimated coefficient, standard error, and weak instrument F-statistic.

[Insert Table 5 Here]

We first assess the robustness of our results by adjusting the estimated standard errors following the approach in Borusyak et al. (2022). In two-stage least squares (2SLS) regressions, standard errors may be invalid if residuals are correlated across firms with similar exposure shares (Adao et al., 2019). To address this, we use the *ssaggregate* Stata command to aggregate the data to the shock level and estimate the IV model accordingly.[16] The shock-level IV regressions (rows (2) and (3)) confirm that our main results remain highly statistically significant after aggregating the data and clustering standard errors in different ways to account for potential correlation across occupation groups. As a complementary check, we also examine whether alternative clustering choices in the firm-level regressions change statistical significance. Clustering at the 3-digit NAICS industry level, as well as the city level to account for possible local spillovers, does not substantially alter the standard errors (rows (4) and (5)).

We next proceed to test the robustness of the estimates to adjusting the regression specifications by adding additional firm- and shock-level controls. Controlling for the time

[16]This method aggregates the outcomes and treatment variables using exposure weights to obtains shock-level data and allows to estimate the IV model using shocks (SOC-level *AI Shares*) directly as instruments. While coefficient estimates remain identical to the firm-level IV results, this approach allows for correct inference by adjusting standard errors for potential correlation across shocks.

fixed effects within 3-digit NAICS industries to account for finer industry-specific trends (row (6)) slightly decreases the magnitude of the coefficients, but they remain statistically and economically significant. To account for the possibility that exposure to other technologies, such as robotics or data analytics, might influence management practices and be correlated with AI adoption, we introduce a series of technology-related controls. First, we add firm-level shares of Robotics, Data, and Cloud Computing skills (row (7)). We then expand this to include ten additional commonly studied skills, such as Software, Computer, Cognitive, and Social skills among others, used in prior literature to characterize job tasks (e.g., Deming & Kahn, 2018) (row (8)). Additionally, we control for the average education and experience requirements in posted vacancies, capturing the overall skill level of the firm's labor demand (row (9)). Descriptive statistics for these firm-level measures are presented in Table A3 in Online Appendix.

We further extend this approach by constructing shift-share analogs of these alternative technologies and skill measures and include them as controls. This allows us to examine whether the estimated effects of AI adoption are uniquely attributable to AI, or whether they instead reflect broader technological or skill-related changes within occupations. Specifically, we apply the same methodology used for constructing the AI instrument, replacing the AI-related shocks with national trends in Robotics, Data, other skill intensity and education and experience requirements (rows (10) to (12)). In all of these specifications, our main IV results remain robust, as reported in Table 5.

Finally, the results are also robust to additional specification checks: adding time-varying financial and operational firm-level controls (row (13)), such as the natural logarithm of firm sales, the natural logarithm of firm employment, cash-to-assets ratio, R&D intensity, and the physical capital intensity; excluding companies with highly concentrated occupational structures defined as firms with the HHI index of the their occupational shares above 0.1 (row (14)); reestimating the instrument using the leave-one-out approach (row (15)); and varying the measurement of *AI Share* or the demand for managers. For instance, we check the

sensitivity of results to defining managerial roles using job titles, rather than relying on the occupational classification provided by Lightcast (row (16)), excluding AI-related vacancies from the computation of *Managers Share* and *Ln(Managerial Vacancies)* (row (17)), and using alternative measures of AI adoption based on firms' average continuous scores of job AI-relatedness (row (18)) or keyword-based definition of *AI Share* (row (19)) described in Section 3.1. Excluding Finance sector (row (20)) or top five percent of AI adopters (row (21)) also does not qualitatively alter our results. Across all of these robustness checks, the IV coefficient estimates remain stable in magnitude and statistically significant, reinforcing the credibility of our identification strategy.

5.1.3 Heterogeneity analysis

While the main results showed that AI adoption is associated with increased intensity in the demand for managers, this relationship may not be uniform across all firms and industries. In this section, we explore how the effect varies depending on the industry context, firm characteristics, and the types of managers. By exploring this heterogeneity, we aim to better understand the conditions under which AI complements managerial roles and how organizational responses differ across settings.

Table 6 explores the impact of AI adoption on the demand for managers across different industries. Manufacturing is the sector that exhibits the largest increase in managerial vacancies, both in absolute terms and as a share of total vacancies. In contrast, Finance, Trade, and the remaining industries grouped under "Other" show less consistent patterns. Although the IV coefficients for Finance and Other are positive, their standard errors are large. These results suggest that the overall impact of AI adoption on managerial demand varies significantly by sector: while AI can, in theory, both substitute for and complement managerial roles, in Manufacturing the complementarity effects dominate, leading to a clear rise in managerial demand, whereas in other sectors, the two forces appear more balanced.

[Insert Table 6 Here]

To further explore the variation in the effect across various firm categories, Table 7 examines heterogeneity in the effect of AI adoption across firms with different characteristics (presents only IV regression results). We split the sample along three dimensions: firm size (proxied by sales), R&D activity, and Software skill intensity. The results show that the effect of AI on managerial demand is similar across high-sales and low-sales firms, though the estimates are more precise in the larger-firm subsample, where standard errors are smaller. This suggests that firm size is not a major driver of variation in the magnitude of the effect. In contrast, innovation activity and technological capability appear to play a more important role. Among firms that report R&D expenditures, the effect of AI adoption on managerial demand is both large and statistically significant, while the effect is smaller and has large standard errors in firms without R&D. This pattern is even more pronounced when the sample is split by Software skill intensity: firms with a high share of Software-related skills experience a strong and significant increase in managerial demand, whereas the effect is near zero and insignificant in firms with low Software skill intensity. Together, these results suggest that managerial complementarity with AI technologies is especially strong in firms that are innovation-oriented or already possess substantial IT capabilities.

[Insert Table 7 Here]

Finally, we investigate whether AI adoption disproportionately affects certain types of managerial roles, using detailed occupational classifications. We categorize managerial vacancies into four groups based on the 3-digit SOC codes: Executives (SOC "11-1"), Marketing and Sales Managers (SOC "11-2"), Operations Managers (SOC "11-3"), and Other Managers (SOC "11-9"), which includes smaller categories or unclassified managerial vacancies. Results in Online Appendix Table A7 show that no single managerial category experiences a statistically significant increase in demand relative to others. This suggests that the rise in managerial demand due to AI adoption is broad-based across different management functions.

Taken together, these results indicate that the effects of AI adoption on managerial

demand are strongest in firms with highly interdependent operations, as is the case in the manufacturing sector, and in technologically advanced and innovation-oriented settings, possibly due to the need to manage more complex environments in such organizations. Also, this effect extends across a wide range of managerial functions, reflecting a broad organizational change.

5.2 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. Prior analysis showed the change in the intensity of the demand for managers, especially in organizations that might have more complex processes. However, an equally important question is how the content of managerial roles evolves. In other words, does AI adoption simply increase the number and share of managers, or does it fundamentally change what managers are expected to do?

We now analyse how the profile of managers in terms of frequently required skills is changing with the adoption of AI. Figure 2 presents this analysis, focusing on skills that are most strongly affected, positively and negatively, based on 2SLS regressions. While not all estimated effects can be interpreted causally due to the presence of pre-trends in some skills (marked in the figure), a clear pattern emerges. Among the skills positively affected by AI adoption in the overall sample (Panel A) are Sales, Sales Management, Sales Goals, Procurement, Listening, and Written Communication, indicating a shift toward skills that support company growth and coordination. In contrast, the results point to a decline in the demand for several traditional and routine managerial capabilities, including Budgeting, Microsoft Office proficiency, Staff Management, Customer Service, and Strategic Planning. A decline is also observed for Physical Abilities, suggesting that AI may be contributing to the reduced relevance of manual aspects of managerial work. Interestingly, we also observe a decreasing requirement for Building Effective Relationships, which might indicate a switch toward more formal or systems-based management styles. Results from the later part of the

sample (2016—2022) show consistent patterns, with Data Analysis and Quality Assurance also appearing as positively affected by AI adoption (Figure A5 in Online Appendix).

[Insert Figure 2 Here]

This transformation is particularly pronounced in the manufacturing sector, where the increase in managerial demand intensity is the strongest. When focusing on managerial skill content within manufacturing job postings, in Panel B of Figure 2, we observe a clear shift toward strategic and problem-solving capabilities. Excluding skills with significant pre-trends, the most positively affected skills include Creativity, Sales, Teamwork and Collaboration, Stakeholder Management, Sales Management, Merchandising, Inventory Management, Problem Solving, Training Programs, and Listening. At the same time, the demand for traditional skills such as Physical Abilities, Budgeting, Performance Appraisals and Analysis, Planning, Scheduling, Building Effective Relationships, and Customer Service declines even more sharply than in the overall sample. This suggests that in manufacturing, AI may be actively replacing the more routine or operational aspects of managerial work while elevating the strategic role of managers.[17]

Overall, the evidence underscores the transformative effect of AI on managerial work, which not only increases the demand for managers in many contexts, but also reshapes the skills that define managerial effectiveness. As routine and administrative tasks are becoming increasingly automated, the value of strategic, growth-oriented, and coordination-focused skills becomes more central to managerial roles.[18]

Online Appendix Figures A6 and A7 present the results for all the top 100 most required skills in managerial jobs. These figures expand on the earlier analysis and illustrate the breadth of AI's influence on managerial roles, promoting higher-order skills, phasing out

[17] Online Appendix Figure A8 presents the managerial skills most strongly affected by AI adoption in other broad industry groups.

[18] We also examine whether firms adopting AI more intensively also increase hiring of AI-skilled managers. Table A9 shows that a one-percentage-point increase in non-managerial AI vacancies is associated with a 0.73 percentage point rise in the share of AI-skilled managers—a 61 percent increase relative to the mean (1.2 percent). However, there is no significant increase in their absolute number, suggesting that firms primarily rely on generalist managers to oversee AI-related functions.

more routine and traditional competencies, while leaving some core managerial competencies (e.g., Organizational Skills, Financial management, Oral Communication, Mentoring) largely unaffected. This reinforces the view that AI is reshaping, but not uniformly replacing, managerial work.

To complement this analysis, we now examine whether these changes are reflected in posted wages, which would indicate whether managers are becoming more valuable within organizations. If managers are expected to enhance productivity by complementing AI technology, we would expect firms with higher *AI Share* to offer higher salaries for managerial roles. However, Online Appendix Table A10 (columns (1) and (2)) shows that while *AI Share* is positively correlated with managerial pay in the OLS regression, the causal effect of AI adoption on wages is close to zero in the IV specification. Moreover, there is no evidence of a relative increase in managerial salaries compared to those of non-managerial employees.[19] Overall, we find no evidence that AI adoption raises managerial pay. Nevertheless, while some traditional managerial tasks appear to be automated, managers remain a highly paid segment of the workforce, with no indication that AI is substituting these roles.

6 CONCLUSION

This paper has sought to resolve a core tension in the literature regarding the impact of AI on the managerial workforce. Contrary to perspectives that frame AI primarily as a tool for substitution, our large-scale, firm-level evidence reveals a story of reconfiguration and complementarity. Using a quasi-experimental design, we show that AI adoption is causally associated with an increase in firms' demand for managers, both in share and in absolute numbers. In our IV estimates, a one-percentage-point rise in *AI Share* raises *Managers Share* by about 1.2 percentage points and managerial vacancies by roughly nine percent. This effect is concentrated in firms with strong dynamic capabilities, specifically, those with

[19]These results are based on relatively limited salary data from Lightcast. Although we require only five managerial and five non-managerial vacancies with salary data per company-year, the sample size is reduced by about 50 percent.

R&D and high software-skill intensities, and is most pronounced in manufacturing.

Our findings yield two primary contributions to strategy research on technology and organization co-evolution. First, we provide causal, firm-level evidence that, on the margin, AI acts as a complement to managerial labor, especially in capability-rich firms, rather than a uniform substitute. We sharpen this by showing that complementarity is contingent on firm capabilities, suggesting that the value of AI is unlocked not just through its adoption, but through a firm's ability to reconfigure its organization to exploit it. This qualifies analogies to prior automation waves that emphasized labor substitution.

Second, we document a fundamental shift in the *content* of managerial work. As AI automates routine administrative tasks, firms increase their demand for managers with growth-oriented and interpersonal skills. Consistent with this, postings tilt toward coordination and growth capabilities and away from routine administrative requirements. Notably, we do not observe a corresponding surge in the *count* of AI-specialist managers; firms appear to rely predominantly on generalist managers to oversee AI functions. Despite task substitution at the margin, we find no causal effect of AI adoption on posted managerial wages (recognizing the limited coverage of salary data).

Our study has implications for theory and practice. For scholars, it underscores the need to move beyond automation-versus-augmentation debates toward a co-evolution of technology and organizations, one that highlights firm capabilities and operating context. For practitioners, the message is clear: the strategic benefits of AI are not realized by simply replacing labor, but by investing in the complementary managerial capital required to lead an AI-augmented workforce.

In conclusion, the age of AI is unlikely to be an age without managers. Rather, it will be an age that demands a new *type* of manager, one who orchestrates human–AI ensembles, governs risk, and translates technological possibilities into scalable economic value.

REFERENCES

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293–S340.

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108*(6), 1488–1542.

Adao, R., Kolesár, M., & Morales, E. (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, *134*(4), 1949–2010.

Afuah, A., & Tucci, C. L. (2012). Crowdsourcing as a solution to distant search. *Academy of Management Review*, *37*(3), 355–375.

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for ai skills in the labor market. *Labour economics*, *71*, 102002.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., & Shu, P. (2020). Foreign competition and domestic innovation: Evidence from us patents. *American Economic Review: Insights*, *2*(3), 357–374.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, *151*, 103745.

Bardhan, I., Krishnan, V., & Lin, S. (2013). Research note—business value of information technology: Testing the interaction effect of it and rd on tobins q. *Information Systems Research*, *24*(4), 1147–1161.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?

Berg, J. M., Raj, M., & Seamans, R. (2023). Capturing value from artificial intelligence. *Academy of Management Discoveries*, *9*(4), 424–428.

Bloom, N., Garicano, L., Sadun, R., & Van Reenen, J. (2014). The distinct effects of information technology and communication technology on firm organization. *Management Science*, *60*(12), 2859–2885.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of economic studies*, *89*(1), 181–213.

Borusyak, K., Hull, P., & Jaravel, X. (2025). A practical guide to shift-share instruments. *Journal of Economic Perspectives*, *39*(1), 181–204.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, *117*(1), 339–376.

Brynjolfsson, E., Hitt, L. M., & Yang, S. (2002). Intangible assets: Computers and organizational capital. *Brookings Papers on Economic Activity*, *2002*(1), 137–198. (Brookings Institution Press.)

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn and what does it mean for occupations and the economy? In *Aea papers and proceedings* (Vol. 108, pp. 43–47).

Carnevale, A. P., Jayasundera, T., & Repnikov, D. (2014). Understanding online job ads data. *Georgetown University, Center on Education and the Workforce, Technical Report (April)*.

Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2025). Human-ai ensembles: When can they work? *Journal of Management*, *51*(2), 536–569.

Csaszar, F. A., Ketkar, H., & Kim, H. (2024). Artificial intelligence and strategic decision-making: Evidence from entrepreneurs and investors. *Strategy Science*, *9*(4), 322–345.

Deming, D. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), 1593–1640.

Deming, D., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, *36*(S1), S337–S369.

Dessein, W., Garicano, L., & Gertner, R. (2010). Organizing for synergies. *American Economic Journal: Microeconomics*, *2*(4), 77–114.

Dixon, J., Hong, B., & Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. *Management Science*, *67*(9), 5586–5605.

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, *42*(12), 2195–2217.

Furman, J., & Seamans, R. (2019). Ai and the economy. *Innovation Policy and the Economy*, *19*, 161-191.

Garicano, L. (2000). Hierarchies and the organization of knowledge in production. *Journal of Political Economy*, *108*(5), 874–904.

Goldfarb, A., Taska, B., & Teodoridis, F. (2023). Could machine learning be a general purpose technology? a comparison of emerging technologies using data from online job postings. *Research Policy*, *52*(1), 104653.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2018). *Bartik instruments: What, when, why, and how* (Tech. Rep.). National Bureau of Economic Research.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109–122.

Gulati, P., Marchetti, A., & Puranam, P. (2023). Digital collaboration technologies and managerial intensity in us corporations: An examination.

Hampole, M., Papanikolaou, D., Schmidt, L. D. W., & Seegmiller, B. (2025, February). *Artificial intelligence and the labor market* (Tech. Rep. No. Working Paper 33509). National Bureau of Economic Research.

Hasan, S., Oettl, A., & Samila, S. (2025, June). *From model design to organizational design: Complexity redistribution and trade-offs in generative ai.* (Available at SSRN. Version of June 10, 2025.)

Hershbein, B., & Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, *108*(7), 1737–72.

Hillebrand, L., Raisch, S., & Schad, J. (2025). Managing with artificial intelligence: An integrative framework. *Academy of Management Annals*, *19*(1), 343–375.

Huang, M.-H., Rust, R., & Maksimovic, V. (2019). The feeling economy: Managing in the next generation of artificial intelligence (ai). *California Management Review*, *61*(4), 43–65.

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the age of ai: Strategy and leadership when algorithms and networks run the world.* Boston, MA: Harvard Business Review Press.

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments

employee creativity. *Academy of Management Journal*, *67*(1), 5–32.
Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410.
Kim, H., Glaeser, E. L., Hillis, A., Kominers, S. D., & Luca, M. (2024). Decision authority and the returns to algorithms. *Strategic Management Journal*, *45*(4), 619–648.
Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *44*(6), 1425–1452. (Special Issue Article. Published online 16 February 2022.) doi: 10.1002/smj.3387
Lane, M. (2024, October). *Who will be the workers most affected by ai? a closer look at the impact of ai on women, low-skilled workers and other groups* (Tech. Rep. No. 26). Paris: OECD Publishing. (October 2024. Creative Commons Attribution 4.0 International (CC BY 4.0).)
Law, K. K. F., & Shen, M. (2024). How does artificial intelligence shape audit firms? *Management Science*, *71*(5), 3641–3666.
Lei, Y.-W., & Kim, R. (2024). Automation and augmentation: Artificial intelligence, robots, and work. *Annual Review of Sociology*, *50*, 251–272.
Milgrom, P., & Roberts, J. (1990). The economics of modern manufacturing: Technology, strategy, and organization. *American Economic Review*, *80*(3), 511–528.
National Institute of Standards and Technology. (2023). *Artificial intelligence risk management framework (ai rmf 1.0)* (Tech. Rep. No. NIST AI 100-1). National Institute of Standards and Technology. Retrieved from `https://doi.org/10.6028/NIST.AI.100-1` (U.S. Department of Commerce, January 2023)
Pinsonneault, A., & Kraemer, K. L. (1997). Middle management downsizing: An empirical investigation of the impact of information technology. *Management Science*, *43*(5), 659–679.
Porter, M. E. (1996). What is strategy? *Harvard Business Review*, *74*(6), 61–78.
Rajan, R. G., & Wulf, J. (2006). The flattening firm: Evidence from panel data on the changing nature of corporate hierarchies. *Review of Economics and Statistics*, *88*(4), 759–773. (Publisher: MIT Press)
Shanthikumar, D. M., & Yoo, I. S. (2024, November). *Artificial intelligence and analyst productivity.* Retrieved from `https://ssrn.com/abstract=5040339` (SSRN Working Paper No. 5040339)
Tambe, P. (2014). Big data investment, skills, and firm value. *Management Science*, *60*(6), 1452–1469.
Tambe, P., & Hitt, L. M. (2012). The productivity of information technology investments: New evidence from it labor data. *Information Systems Research*, *23*(3-part-1), 599–617.
Tambe, P., Hitt, L. M., & Brynjolfsson, E. (2012). The extroverted firm: How external information practices affect innovation and productivity. *Management Science*, *58*(5), 843–859.
Tambe, P., Hitt, L. M., Rock, D., & Brynjolfsson, E. (2019). It, ai and the growth of intangible capital. *Available at SSRN 3416289*.
Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.
Thompson, J. D. (1967). *Organizations in action: Social science bases of administrative*

theory. New York: McGraw-Hill.

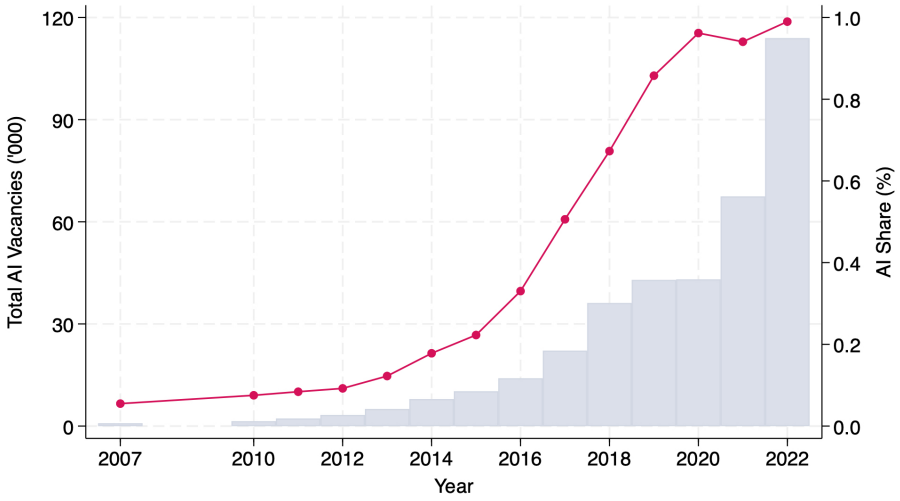
Tolan, S., Pesole, A., Martínez-Plumed, F., Fernández-Macías, E., Hernández-Orallo, J., & Gómez, E. (2021). Measuring the occupational impact of ai: tasks, cognitive abilities and ai benchmarks. *Journal of Artificial Intelligence Research*, *71*, 191–236.

Vanneste, B. S., & Puranam, P. (in press). Artificial intelligence, trust, and perceptions of agency. *Academy of Management Review*. (Accepted for publication. Pre-print dated 24 January 2024.)

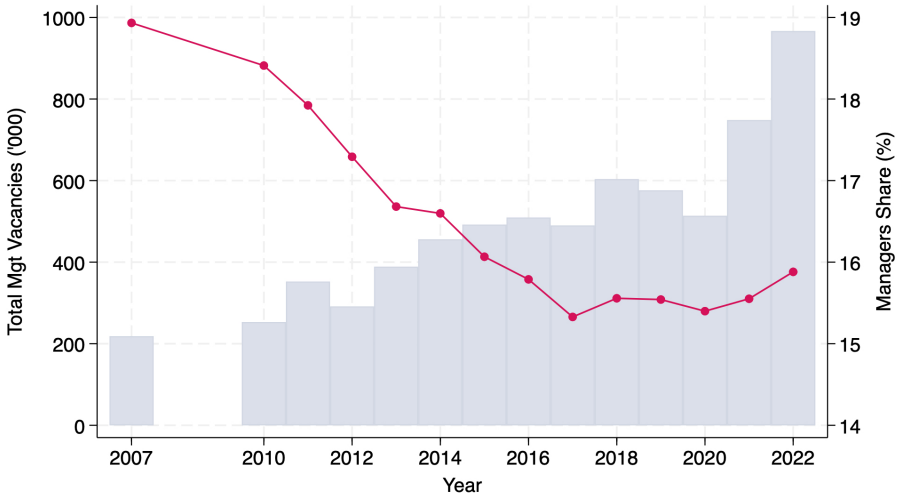
Webb, M. (2019). The impact of artificial intelligence on the labor market. *Available at SSRN 3482150*.

Zammuto, R. F., & O'Connor, E. J. (1992). Gaining advanced manufacturing technologies' benefits: The roles of organization design and culture. *Academy of Management Review*, *17*(4), 701–728.

FIGURE 1 Vacancies Demanding AI Skills and Managers over Time. Panel A shows the total number of AI-related vacancies posted by firms in the analyzed sample (bars) and the average *AI Share* of these firms (line) over time. Panel B shows the corresponding trends for managerial vacancies (defined using 2-digit SOC code 11): the total number of managerial vacancies posted by all firms in the analyzed sample (bars) and the average *Managers Share* (line) of firms over time.

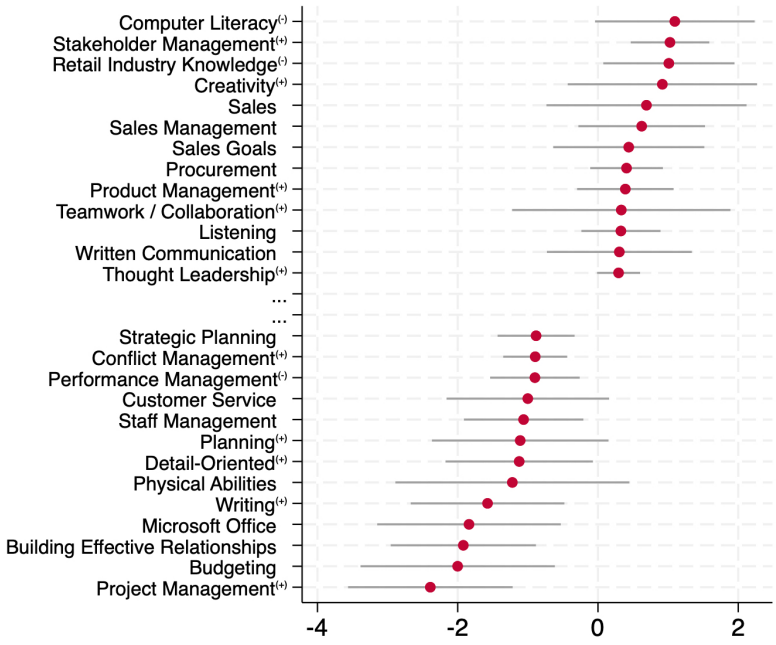


Panel A: AI Vacancies.

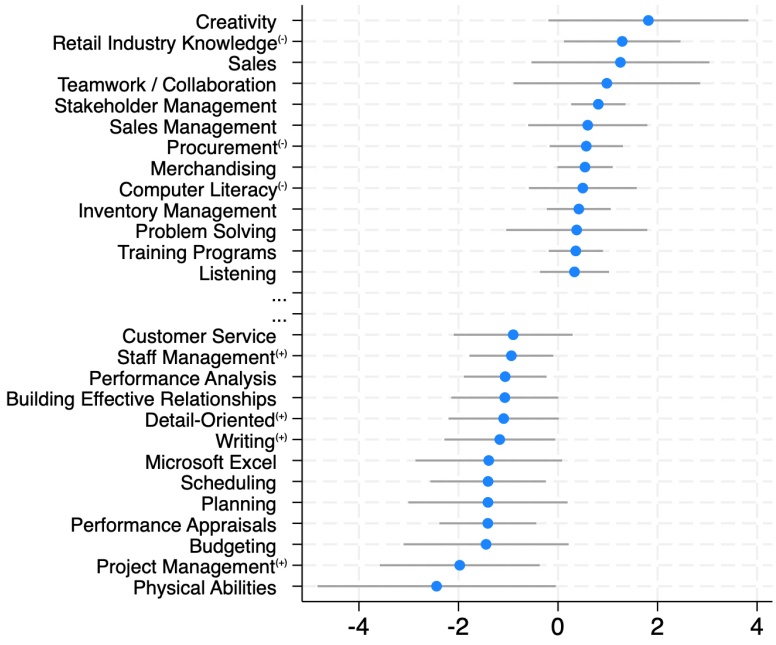


Panel B: Managerial Vacancies.

FIGURE 2 AI Adoption and the Demand for Skills (Most Affected Skills). The figure shows coefficients estimated in 2SLS regressions following specification 2. Circles represent the coefficient estimates and horizontal bars represent 95 percent confidence intervals. The data used includes firm-year observations with at least 30 managerial vacancies. All coefficient estimates are multiplied by a 100. Superscripts indicate variables that showed signs of pre-trends over 2007–2010, with (+) and (-) indicating positive and negative pre-trends, respectively.



Panel A: Overall Sample.



Panel B: Manufacturing Sector.

TABLE 1 Summary statistics.

Panel A: Data at the Firm-Year Level:

	Obs.	Firms	Mean	SD	p(5)	p(50)	p(95)
Key Vacancy-based Measures:							
AI Share	9,876	823	0.5%	1.2%	0.0%	0.0%	2.6%
No. AI Vacancies	9,876	823	37	359	0	0	101
Managers Share	9,876	823	16.1%	9.4%	2.7%	15.1%	34.2%
No. Managerial Vacancies	9,876	823	647	1,892	16	170	2,581
No. Total Vacancies	9,876	823	5,203	15,537	139	1,215	22,148
Skill Shares within Managerial Vacancies:							
Communication Skills	9,858	823	49.3%	20.4%	12.0%	50.4%	82.4%
Budgeting	9,858	823	29.4%	17.5%	3.5%	27.7%	62.0%
Planning	9,858	823	27.8%	15.4%	2.8%	27.7%	54.9%
Teamwork / Collaboration	9,858	823	26.2%	18.1%	0.5%	24.1%	59.0%
Project Management	9,858	823	23.0%	15.3%	0.6%	22.4%	50.0%
Problem Solving	9,858	823	22.8%	15.9%	0.7%	20.5%	53.6%
Microsoft Excel	9,858	823	22.8%	16.7%	1.8%	19.4%	56.3%
Microsoft Office	9,858	823	19.2%	17.1%	0.2%	14.6%	54.4%
Scheduling	9,858	823	18.6%	15.3%	0.9%	14.7%	50.0%
Organizational Skills	9,858	823	18.1%	13.8%	1.5%	15.2%	46.3%
Shift-Share IV:							
Shift-Share IV Value	9,876	823	0.6%	0.6%	0.0%	0.3%	1.9%

Panel B: Data Aggregated to the SOC Level:

Mean AI Share	0.3%
St. Dev. of AI Share	2.5%
Interquartile range of AI Share	0.1%
HHI of weights	0.001
Effective sample size (1/HHI)	778
Largest weight	0.5%
No. of 5-digit SOC	782

Note: Panel A reports descriptive statistics for a balanced sample at the company-year level. The sample includes matched Compustat-Lightcast data. IT companies, companies that have fewer than 50 vacancies per year, and companies with missing data for variables used in the analysis are excluded. All ratios are winsorized at 1 and 99 percent. Panel B reports the descriptive statistics at the 5-digit SOC-year level obtained in the result of aggregating the firm-level data to the shock level using the *ssaggregate* Stata command (Borusyak et al., 2022).

TABLE 2 Pre-Trend Tests.

Panel A. Pre-trends in Managers Share:

	Δ Managers Share (2007–2010)				
	(1)	(2)	(3)	(4)	(5)
Δ IV (2011–2022)	0.005				
	(0.011)				
Δ IV (2011–2015)		0.005			
		(0.035)			
Δ IV (2016–2022)			0.009		
			(0.018)		
Δ SOC-level AI Share (2011–2022)				0.027	0.027
				(0.034)	(0.051)
Observations	521	521	521	770	770
R-squared	0.111	0.110	0.112	0.002	0.002
Ln(Vacancies, 2007) control	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Standard errors	Cluster 2d Ind	Cluster 2d Ind	Cluster 2d Ind	Robust	Cluster SOC2

Panel B. Pre-trends in Num. Managerial Vacancies:

	Δ Ln(Managerial Vacancies) (2007–2010)				
	(1)	(2)	(3)	(4)	(5)
Δ IV (2011–2022)	-0.029				
	(0.062)				
Δ IV (2011–2015)		-0.067			
		(0.181)			
Δ IV (2016–2022)			-0.053		
			(0.105)		
Δ SOC-level AI Share (2011–2022)				-0.198	-0.198
				(0.196)	(0.219)
Observations	519	519	519	770	770
R-squared	0.155	0.154	0.155	0.001	0.001
Ln(Vacancies, 2007) control	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Standard errors	Cluster 2d Ind	Cluster 2d Ind	Cluster 2d Ind	Robust	Cluster SOC2

Note: The table presents regression results for a specification where the dependent variable is the pre-period (2007–2010) change in the share or number of managerial vacancies, and the independent variable is the post-period change in the value of the instrument. Standard errors are clustered at the 2-digit NAICS industry in columns (1) to (3), reported as robust in column (4), and clustered at the 2-digit SOC level in column (5); all standard errors are presented in parentheses.

TABLE 3 AI Adoption and the Demand for Managers.

	Managers Share		Ln(Managerial vacancies)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.003	0.012	0.030	0.090
	(0.001)	(0.004)	(0.007)	(0.030)
Observations	9,876	9,876	9,863	9,863
R-squared	0.778		0.947	
F-stat for weak IV		89.77		89.54
Ln(Vacancies) control	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓

Note: The table presents regression results for equation 1, with the dependent variable equal to *Managers Share* in columns (1) and (2), and the natural logarithm of managerial vacancies in columns (3) and (4). Standard errors clustered at the company level are reported in parentheses.

TABLE 4 AI Adoption and the Demand for Vacancies - Gradual Controls.

Included controls	OLS/IV	Managers Share		Ln(Mgt Vacancies)		Ln(Total Vacancies)		Ln(Non-Mgt Vacancies)	
		Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unconditional on Labor Demand:									
No	OLS	0.011	(0.006)	0.179	(0.042)	0.089	(0.033)	0.058	(0.036)
No	IV	0.039	(0.013)	0.096	(0.049)	-0.182	(0.090)	-0.249	(0.102)
Size	OLS	0.011	(0.006)	0.027	(0.028)	-0.056	(0.034)	-0.088	(0.038)
Size	IV	0.040	(0.013)	-0.027	(0.113)	-0.307	(0.172)	-0.375	(0.182)
Firm FE	OLS	0.004	(0.001)	0.004	(0.017)	-0.030	(0.017)	-0.050	(0.017)
Firm FE	IV	0.013	(0.004)	0.052	(0.055)	-0.043	(0.049)	-0.077	(0.050)
Firm FE + Size	OLS	0.004	(0.001)	-0.003	(0.016)	-0.036	(0.016)	-0.056	(0.016)
Firm FE + Size	IV	0.012	(0.004)	-0.003	(0.049)	-0.091	(0.044)	-0.124	(0.045)
Conditional on Labor Demand:									
Firm FE + Size + Ln(Total Vacancies)	OLS	0.003	(0.001)	0.027	(0.007)				
Firm FE + Size + Ln(Total Vacancies)	IV	0.011	(0.004)	0.075	(0.030)				

Note: The table presents regression results for equation 1, including coefficient estimates and corresponding standard errors for the following dependent variables: *Managers Share* in columns (1) and (2); the natural logarithm of managerial vacancies in columns (3) and (4); the natural logarithm of total vacancies in columns (5) and (6); and the natural logarithm of non-managerial vacancies in columns (7) and (8). The control variables include the natural logarithm of Sales to proxy for company size and the natural logarithm of total vacancies as a control for the overall labor demand. Standard errors clustered at the company level are reported in parentheses.

TABLE 5 Summary of Robustness Tests.

		Managers Share			Ln(Managerial Vacancies)		
Regression Type	SE Clustering	AI Share Coef.	SE	F-stat for IV	AI Share Coef.	SE	F-stat for IV
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IV-Related Robustness:							
(1) Baseline	Firm	0.012	(0.004)	89.77	0.090	(0.030)	89.54
(2) Shock-level Regressions	Robust	0.012	(0.003)	16.84	0.090	(0.023)	16.84
(3) Shock-level Regressions	2-digit SOC	0.012	(0.004)	67.31	0.090	(0.028)	67.31
(4) Baseline	Industry	0.012	(0.004)	141.8	0.090	(0.024)	139.9
(5) Baseline	City	0.012	(0.004)	80.09	0.090	(0.031)	79.83
(6) 3d Industry-Year FE	Firm	0.010	(0.005)	65.26	0.068	(0.041)	65.09
(7) Tech Levels	Firm	0.017	(0.005)	52.22	0.121	(0.044)	52.12
(8) Tech & Skills Levels	Firm	0.018	(0.005)	55.36	0.136	(0.041)	55.15
(9) Tech & Skills & Edu & Exp Levels	Firm	0.018	(0.005)	55.33	0.134	(0.042)	55.11
(10) Tech Shift-share	Firm	0.011	(0.004)	54.14	0.087	(0.035)	53.96
(11) Tech & Skills Shift-share	Firm	0.009	(0.005)	52.20	0.088	(0.040)	52.09
(12) Tech & Skills & Edu & Exp Shift-share	Firm	0.011	(0.005)	46.31	0.090	(0.045)	46.23
(13) Financial Controls	Firm	0.011	(0.004)	71.42	0.076	(0.033)	71.37
(14) Drop Large HHI of Exposure Shares	Firm	0.012	(0.004)	57.11	0.105	(0.034)	57.11
(15) Leave One Out (Firm's Industry)	Firm	0.013	(0.004)	86.86	0.092	(0.031)	86.61
Robustness to Measurement and Sample Adjustments:							
(16) Using Job Titles to Define Managers	Firm	0.020	(0.005)	89.77	0.075	(0.026)	89.77
(17) Exclude AI Managers	Firm	0.011	(0.004)	89.77	0.081	(0.031)	89.54
(18) Continuous AI Share	Firm	0.051	(0.016)	60.78	0.356	(0.124)	61.26
(19) Keyword AI Share	Firm	0.011	(0.003)	90.31	0.071	(0.024)	90.24
(20) Exclude Finance Firms	Firm	0.013	(0.004)	69.76	0.090	(0.032)	69.55
(21) Exclude top-5% AI Adopters	Firm	0.025	(0.007)	146.7	0.168	(0.056)	145.8

Note: The table presents regression results with the dependent variable equal to *Managers Share* or the natural logarithm of managerial vacancies. Column (1) describes the type of the test performed; column (2) specifies the standard error clustering method; columns (3) and (6) report the estimated coefficient of *AI Share*, with the corresponding standard errors shown in columns (4) and (7); columns (5) and (8) present the Kleibergen-Paap F-statistic for the IV.

TABLE 6 AI Adoption and the Demand for Managers - by Industry Group.

Panel A: 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	0.018	0.002	0.010	0.003	-0.011	0.001	0.012
	(0.001)	(0.005)	(0.002)	(0.010)	(0.002)	(0.010)	(0.005)	(0.010)
Observations	4,368	4,368	1,992	1,992	1,272	1,272	2,244	2,244
R-squared	0.759		0.746		0.738		0.767	
F-stat for weak IV		47.87		26.87		7.768		12.64
Ln(Vacancies) control	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: 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	0.035	0.116	0.008	0.090	-0.000	-0.085	0.044	0.117
	(0.007)	(0.029)	(0.011)	(0.065)	(0.037)	(0.123)	(0.035)	(0.119)
Observations	4,367	4,367	1,992	1,992	1,261	1,261	2,243	2,243
R-squared	0.955		0.969		0.899		0.949	
F-stat for weak IV		47.66		26.87		7.760		12.63
Ln(Vacancies) control	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: The table presents regression results for equation 1 with the dependent variable equal to *Managers Share* in Panel A; and the natural logarithm of managerial vacancies in Panel B. The sample is split into broad industry groups based on 2-digit NAICS codes: Manufacturing includes NAICS code 31, 32, and 33; Finance includes codes 52 (Finance and Insurance) and 53 (Real Estate), Trade includes codes 42 (Wholesale Trade) and 44 and 45 (Retail Trade), and Other includes the remaining 2-digit codes. Standard errors clustered at the company level are reported in parentheses.

TABLE 7 AI Adoption and the Demand for Managers - by Firm Characteristics.

Panel A: Change in the Managers Share

	Managers Share					
	By Sales Size		By R&D Investment		By Software Intensity	
	High	Low	Positive	Zero	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share	0.010	0.014	0.018	0.004	0.025	-0.002
	(0.004)	(0.006)	(0.005)	(0.008)	(0.007)	(0.013)
Observations	4,908	4,944	3,912	5,880	4,896	4,932
F-stat for weak IV	52.60	45.28	42.31	31.65	38.20	28.06
Ln(Vacancies) control	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓

Panel B: Change in the Number of Managerial Vacancies

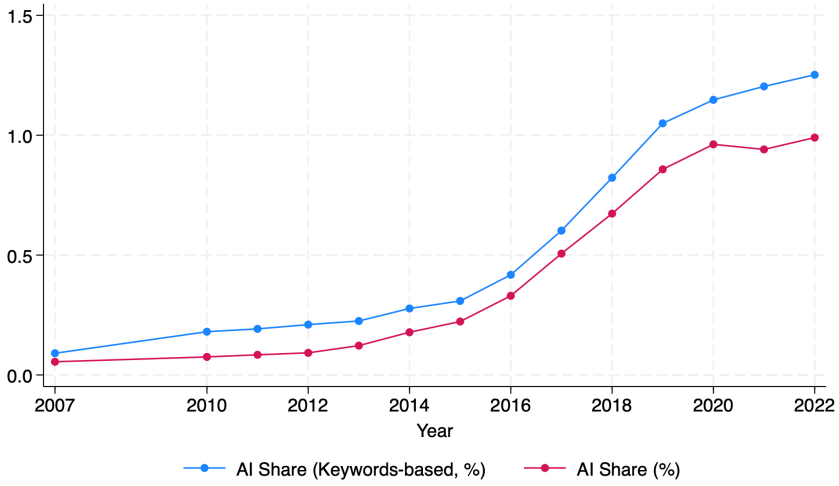
	Ln(Managerial Vacancies)					
	By Sales Size		By R&D Investment		By Software Intensity	
	High	Low	Positive	Zero	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share	0.089	0.090	0.136	0.030	0.168	0.027
	(0.038)	(0.047)	(0.036)	(0.068)	(0.044)	(0.158)
Observations	4,907	4,932	3,911	5,868	4,895	4,920
F-stat for weak IV	52.59	44.91	42.11	31.62	38.03	28.03
Ln(Vacancies) control	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓

Note: The table presents regression results for equation 1, with the dependent variable equal to *Managers Share* in Panel A and the natural logarithm of managerial vacancies in Panel B. The sample is split into groups based on firm size (proxied by sales, using the median value) in columns (1) and (2), R&D activity (based on whether a firm reports R&D expenses) in columns (3) and (4), and Software skill intensity (using the median value) in columns (5) and (6). Standard errors clustered at the company level are reported in parentheses.

Online Appendix for
"AI Adoption and the Demand for Managerial Expertise"
Additional Figures and Tables

FIGURE A1: Share of AI Vacancies, Overall and within Managerial Occupation. Panel A shows the average *AI Share* of firms in the sample estimated using the core method described in Section 3 (red line) and using a keywords-based approach (blue line). Panel B presents the shares of AI vacancies within Management occupation using these two methods. The list of keywords used for the keywords-based approach is presented in Table A1.

Panel A: Overall AI Share.



Panel B. AI Share of Managers.

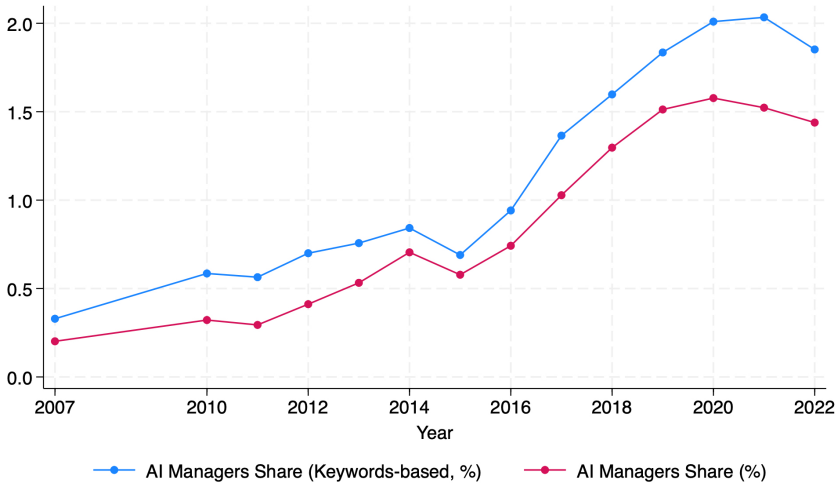
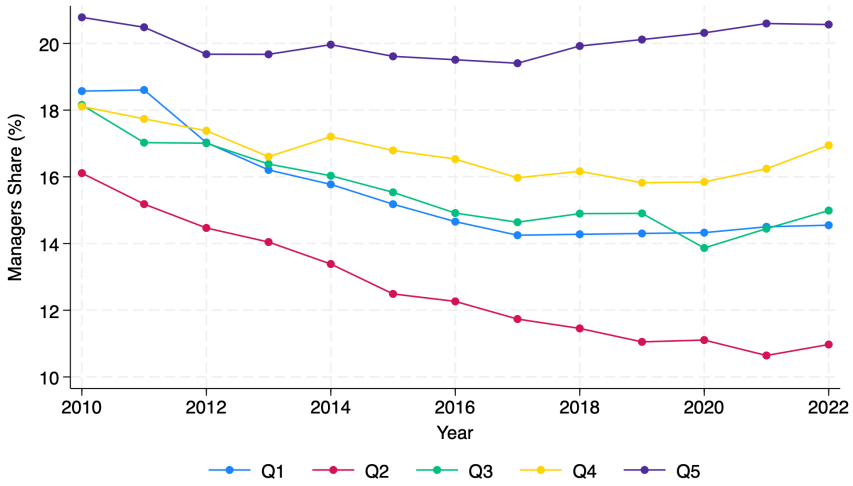


FIGURE A2: Managers Share - by Quintiles of Change in AI Share. The figure shows the evolution of *Managers Share* across groups of companies sorted by the average change in their *AI Share*. "Q1" to "Q5" denote quintiles of the change in *AI Share*, where "Q1" includes firms with the smallest change and "Q5" includes those with the largest. Panel A presents results for the full sample, while Panel B focuses on Manufacturing firms (2-digit NAICS 31, 32, and 33).

Panel A: Managers Share in the Overall Sample.



Panel B. Managers Share in Manufacturing.

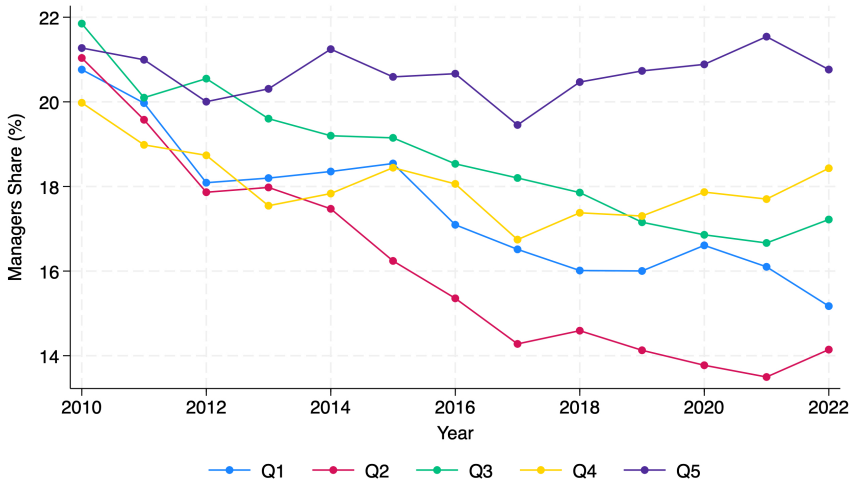
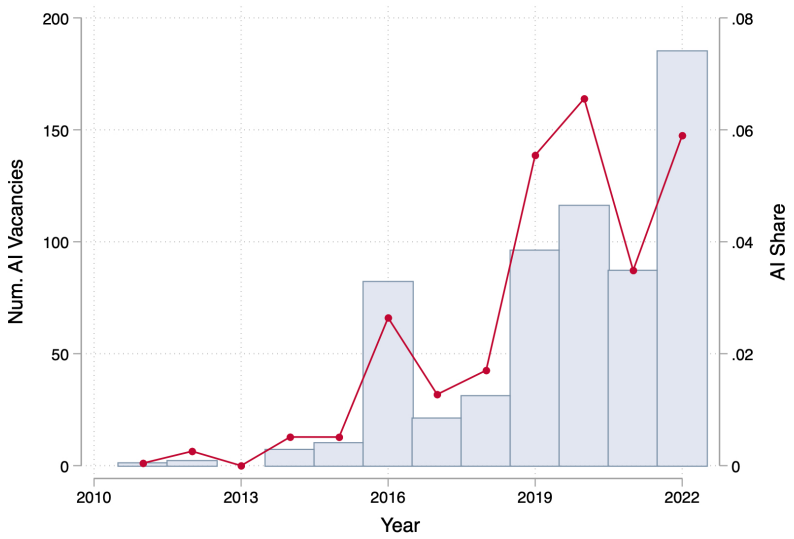


FIGURE A3: Case-study - Procter & Gamble Co. Panel A shows the total number of AI-related vacancies posted by the company (bars) and its average *AI Share* (line) over time. Panel B shows the structure of AI-related vacancies by occupation type over time.

Panel A: AI Hiring.



Panel B. Structure of AI Hiring by Occupations.

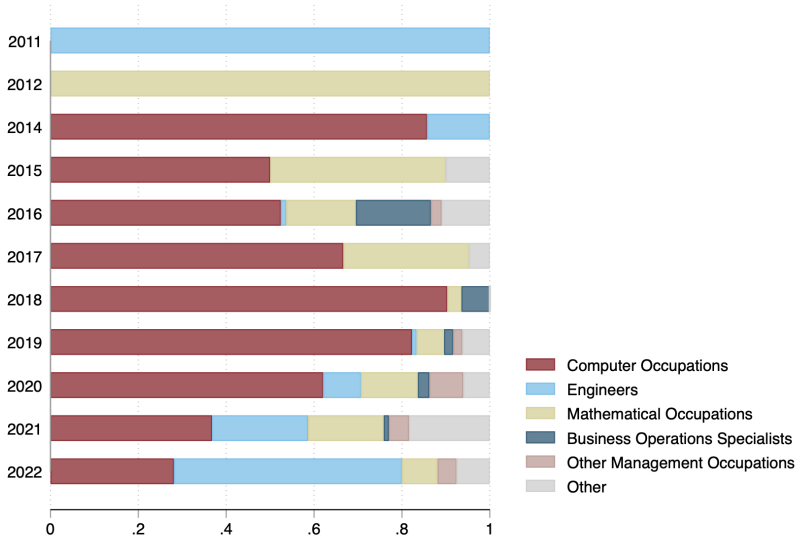
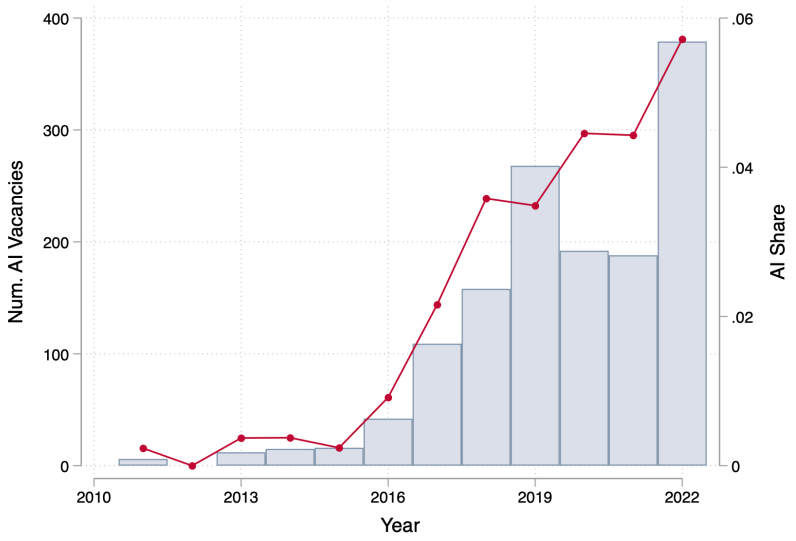


FIGURE A4: Case-study - Amgen. Panel A shows the total number of AI-related vacancies posted by the company (bars) and its average *AI Share* (line) over time. Panel B shows the structure of AI-related vacancies by occupation type over time.

Panel A: AI Hiring.



Panel B. Structure of AI Hiring by Occupations.

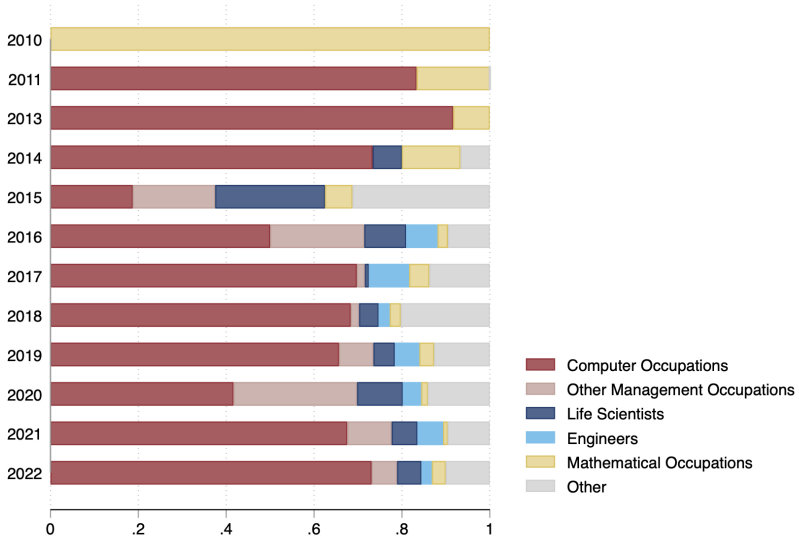


FIGURE A5: AI Adoption and the Demand for Skills - 2016-2022 Period (Most Affected Skills). The figure shows coefficients estimated in 2SLS regressions following specification 2 with a specific *Managerial Skill Share* as the dependent variable, *AI Share* as the independent variable, and the shift-share 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 and only includes firm-year observations with at least 30 managerial vacancies. The figure only presents the most affected skills in managerial vacancies. All coefficient estimates are multiplied by 100 to aid interpretation, with each coefficient directly interpreted as the number of percentage points by which the demand for a given skill share changes in response to a one-percentage-point increase in *AI Share*. Superscripts next to the skill labels indicate variables that showed signs of pre-trends over 2007-2010, with (+) and (-) indicating positive and negative pre-trends, respectively.



FIGURE A6: Change in the Demand for Managerial Skills: Top 50 Skills by Coefficient Magnitude. 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 the shift-share 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 and only includes firm-year observations with at least 30 managerial vacancies. All coefficient estimates are multiplied by 100. Superscripts next to the skill labels indicate variables that showed signs of pre-trends over 2007-2010, with (+) and (-) indicating positive and negative pre-trends, respectively.

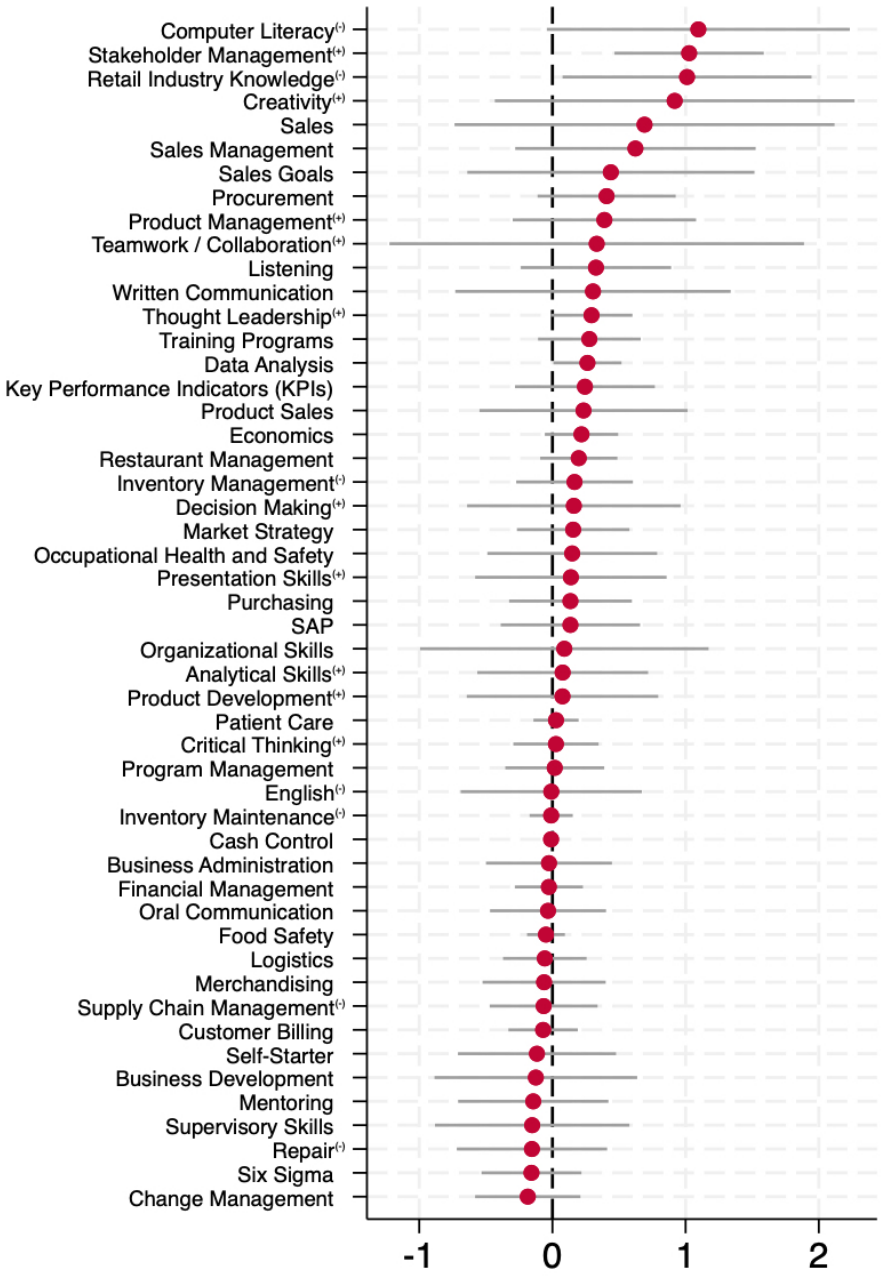


FIGURE A7: Change in the Demand for Managerial Skills: Bottom 50 Skills by Coefficient Magnitude. The figure shows coefficients estimated in 2SLS regressions following specification 2 with a specific *Managerial Skill Share* as the dependent variable, *AI Share* as the independent variable, and the shift-share 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 and only includes firm-year observations with at least 30 managerial vacancies. All coefficient estimates are multiplied by 100. Superscripts next to the skill labels indicate variables that showed signs of pre-trends over 2007-2010, with (+) and (-) indicating positive and negative pre-trends, respectively.



FIGURE A8: Change in the Demand for Managerial Skills: Finance, Trade, and Other Industries.

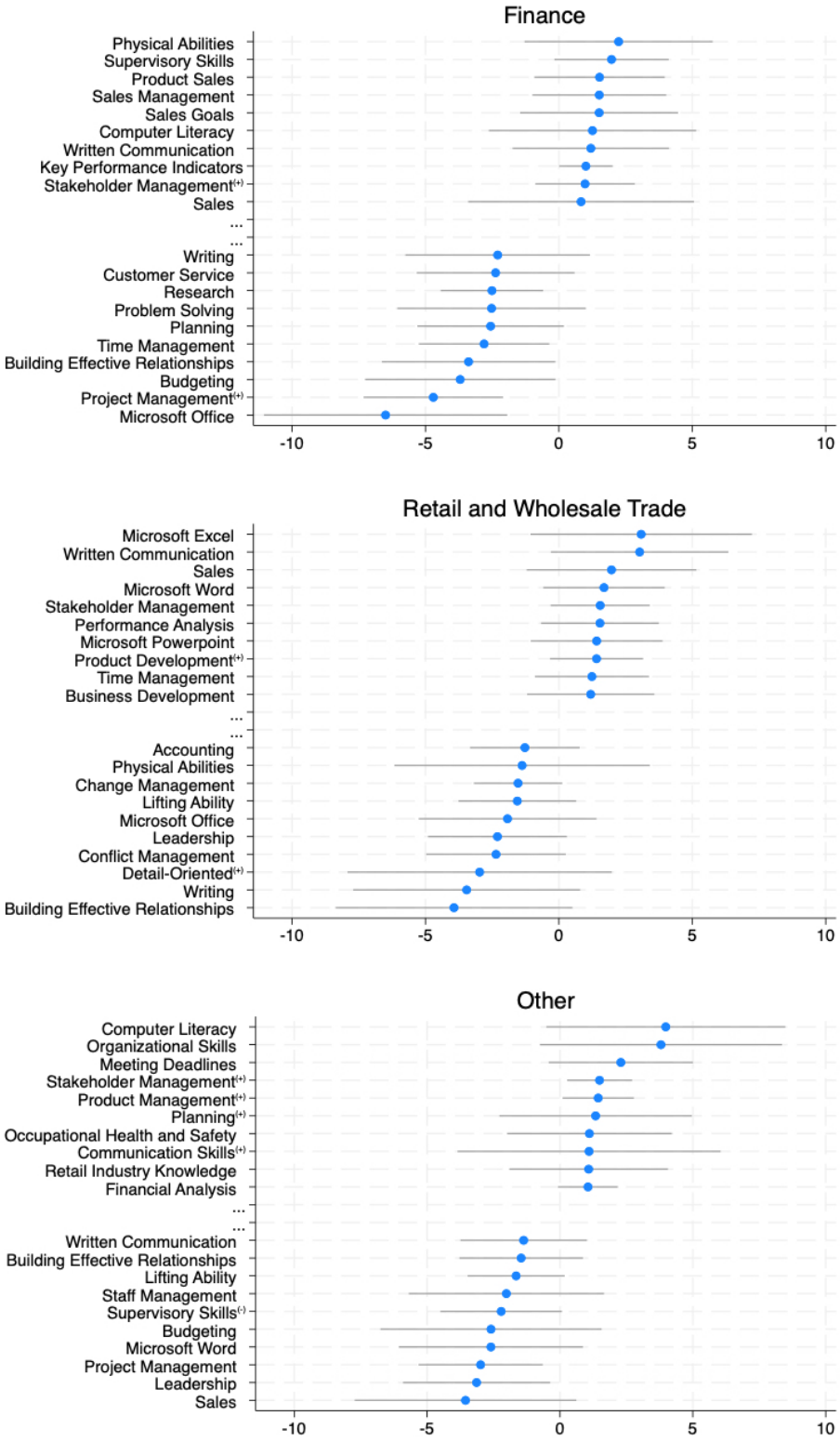


TABLE A1: List of AI Skills. List of skills in the Lightcast job vacancies dataset used to identify AI vacancies according to the keywords-based method.

#	Skill	#	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: Descriptive Statistics - Top Managerial Skills. The table presents descriptive statistics for the 100 most frequently required skills in managerial vacancies posted by companies in the sample. All skill ratios are calculated as the share of a firm's managerial vacancies requiring a specific skill, divided by the total number of the firm's managerial vacancies. All skill ratios are winsorized at 1% and 99%.

#	Skill	Mean	SD	p(50)	#	Skill	Mean	SD	p(50)
1	Communication Skills	49%	20%	50%	51	SAP	5%	9%	0%
2	Budgeting	29%	18%	28%	52	Purchasing	5%	7%	2%
3	Planning	28%	15%	28%	53	Key Performance Indicators	5%	6%	3%
4	Teamwork / Collaboration	26%	18%	24%	54	Project Planning and Development	5%	5%	3%
5	Project Management	23%	15%	22%	55	Self-Starter	5%	6%	3%
6	Problem Solving	23%	16%	21%	56	Meeting Deadlines	5%	7%	3%
7	Microsoft Excel	23%	17%	19%	57	Sales Goals	5%	9%	1%
8	Microsoft Office	19%	17%	15%	58	Mentoring	5%	6%	3%
9	Scheduling	19%	15%	15%	59	Business Administration	5%	7%	3%
10	Organizational Skills	18%	14%	15%	60	Performance Appraisals	5%	8%	2%
11	Building Effective Relationships	16%	13%	13%	61	Performance Analysis	4%	7%	2%
12	Sales	16%	16%	11%	62	Repair	4%	7%	1%
13	Computer Literacy	14%	16%	8%	63	Negotiation Skills	4%	5%	3%
14	Customer Service	13%	14%	9%	64	Business Acumen	4%	6%	2%
15	Written Communication	13%	13%	10%	65	Change Management	4%	5%	3%
16	Detail-Oriented	13%	13%	9%	66	Business Process	4%	5%	3%
17	Writing	12%	12%	10%	67	Marketing	4%	5%	2%
18	Research	12%	10%	10%	68	Financial Analysis	4%	5%	2%
19	Microsoft Powerpoint	12%	11%	10%	69	Occupational Health and Safety	4%	7%	1%
20	Leadership	11%	10%	9%	70	Supply Chain Management	4%	5%	1%
21	Creativity	11%	11%	8%	71	Troubleshooting	4%	5%	2%
22	Staff Management	10%	11%	7%	72	Financial Reporting	4%	5%	2%
23	Presentation Skills	9%	9%	7%	73	Business Strategy	3%	4%	2%
24	Microsoft Word	9%	11%	5%	74	Market Strategy	3%	5%	2%
25	Business Development	8%	10%	6%	75	Conflict Management	3%	5%	2%
26	Physical Abilities	8%	18%	1%	76	Six Sigma	3%	6%	1%
27	Accounting	8%	8%	6%	77	Merchandising	3%	9%	0%
28	Supervisory Skills	8%	11%	4%	78	Stakeholder Management	3%	4%	1%
29	Multi-Tasking	8%	9%	5%	79	Logistics	3%	5%	1%
30	Analytical Skills	7%	8%	5%	80	Program Management	3%	5%	1%
31	Customer Contact	7%	10%	4%	81	Microsoft Project	3%	4%	1%
32	Verbal / Oral Communication	7%	9%	5%	82	Oral Communication	3%	5%	1%
33	Sales Management	7%	11%	3%	83	Inventory Management	3%	6%	1%
34	Time Management	7%	9%	4%	84	Risk Management	3%	5%	1%
35	Quality Assurance and Control	7%	8%	5%	85	Listening	3%	5%	1%
36	Product Development	7%	8%	4%	86	Legal Compliance	3%	4%	1%
37	Quality Management	7%	7%	5%	87	Onboarding	2%	4%	1%
38	Decision Making	6%	8%	4%	88	Economics	2%	4%	1%
39	Retail Industry Knowledge	6%	14%	0%	89	Training Programs	2%	4%	1%
40	Product Management	6%	8%	3%	90	Critical Thinking	2%	4%	1%
41	Business Planning	6%	7%	4%	91	Customer Billing	2%	4%	0%
42	Process Improvement	6%	6%	4%	92	Data Analysis	2%	3%	1%
43	People Management	6%	7%	4%	93	Thought Leadership	2%	3%	0%
44	Performance Management	6%	8%	3%	94	Financial Management	2%	3%	1%
45	Cost Control	6%	7%	3%	95	Lifting Ability	2%	6%	0%
46	Procurement	5%	6%	3%	96	Restaurant Management	1%	6%	0%
47	Product Sales	5%	8%	3%	97	Food Safety	1%	4%	0%
48	Operations Management	5%	8%	3%	98	Inventory Maintenance	1%	2%	0%
49	Strategic Planning	5%	6%	4%	99	Patient Care	1%	4%	0%
50	English	5%	11%	1%	100	Cash Control	0%	1%	0%

TABLE A3: Summary Statistics - Additional Characteristics. The table reports descriptive statistics for additional variables used in the analysis, including firm-level control variables. *Wage* ratios are calculated for each firm-year observation that includes at least five managerial and five non-managerial vacancies with available salary data. All skill ratios are calculated as the share of a firm's vacancies requiring a specific skill, divided by the total number of the firm's vacancies. *Robotics* vacancies are defined as those requesting skill clusters and skills that include the keywords "robotics", "robot", or "mechatronics". *Data*-related vacancies are those requiring skills that include keywords associated with data competencies (e.g., big data, data analysis, data collection, data management, data mining, data science, data storage, distributed computing, and related terms). *Cloud Computing* vacancies include those with skill clusters with keywords "cloud computing", "cloud solutions", "cloud storage" as well as skills with keywords "cloud engineering", "cloud security", "cloud-based", "cloud service", "cloud architecture". The measures for the ten skills from *Software Share* to *Financial Share* are constructed following the approach in Deming and Kahn (2018). Average educational and experience requirements are calculated as the means across vacancies with available data. *Financial* characteristics come from Compustat data. All ratios are winsorized at 1% and 99%.

	Obs.	Firms	Mean	SD	p(5)	p(50)	p(95)
Other Characteristics:							
Mgt/Non-Mgt Wage Ratio	4,502	811	1.5	0.5	0.9	1.4	2.2
Mgt/Non-Mgt Professional Wage Ratio	4,497	811	1.4	0.4	0.8	1.3	2.1
Tech-related Control Variables:							
Data Share	9,876	823	11.6%	9.6%	0.6%	9.6%	30.7%
Robotics Share	9,876	823	0.7%	1.4%	0.0%	0.0%	3.4%
Cloud Computing Share	9,876	823	1.5%	2.6%	0.0%	0.5%	6.6%
Skill-related Control Variables:							
Software Share	9,876	823	28.5%	19.3%	1.9%	26.8%	63.9%
Computer Share	9,876	823	38.0%	19.2%	5.5%	37.8%	71.5%
Cognitive Share	9,876	823	44.7%	20.9%	7.2%	47.6%	75.6%
Social Share	9,876	823	59.2%	21.4%	16.1%	62.3%	89.3%
Character Share	9,876	823	36.4%	18.1%	9.5%	34.6%	70.6%
Writing Share	9,876	823	5.3%	4.5%	0.2%	4.4%	13.9%
Customer Service Share	9,876	823	44.1%	21.9%	13.7%	41.1%	85.7%
Project Management Share	9,876	823	13.5%	10.4%	0.4%	12.1%	32.8%
People Management Share	9,876	823	19.8%	10.8%	4.1%	18.7%	39.0%
Financial Share	9,876	823	27.1%	19.5%	3.7%	22.8%	71.8%
Educational Requirements (years)	9,874	823	12.9	3.2	5.8	13.8	16.1
Experience Requirements (years)	9,876	823	3.9	1.4	1.8	4.0	6.2
Financial Characteristics:							
Sales ($'000)	9,876	823	16,020	37,384	414	4,633	68,711
Employees ('000)	9,876	823	41	108	1	12	167
Cash/Assets Ratio	9,876	823	12%	12%	1%	8%	37%
R&D/Sales Ratio	9,876	823	3%	7%	0%	0%	17%
PPE/Assets Ratio	8,905	748	51%	38%	3%	42%	121%

TABLE A4: Change in Vacancy-based Characteristics. The table presents descriptive statistics for selected variables to illustrate their change over time. It reports average values for the years 2011, 2016, and 2022 (columns (1) to (3)), as well as changes between 2011 and 2016 (column (4)) and between 2016 and 2022 (column (5)). The corresponding t-statistics for the differences in means are reported in columns (5) and (7), respectively.

	2011	2016	2022	Δ 2011-2016		Δ 2016-2022	
	Mean	Mean	Mean	Diff	T-stat	Diff	T-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Key Vacancy-based Measures:							
AI Share	0.1%	0.3%	1.0%	0.2%	(8.3)	0.7%	(9.4)
Management Share	18%	16%	16%	-2%	(-4.5)	0%	(0.2)
Skill Shares within Managerial Vacancies:							
Communication Skills	45%	51%	52%	6%	(5.7)	1%	(0.9)
Budgeting	27%	29%	30%	2%	(2.5)	0%	(0.1)
Planning	24%	28%	31%	4%	(4.7)	3%	(4.3)
Teamwork / Collaboration	17%	26%	35%	9%	(11.7)	9%	(10.1)
Project Management	22%	24%	25%	2%	(2.9)	1%	(1.0)
Scheduling	16%	19%	20%	3%	(4.0)	1%	(1.1)
Problem Solving	18%	23%	26%	5%	(7.2)	3%	(4.4)
Microsoft Excel	20%	24%	24%	4%	(4.4)	0%	(0.3)
Organizational Skills	16%	18%	20%	2%	(2.7)	2%	(3.3)
Microsoft Office	15%	20%	22%	5%	(5.9)	2%	(2.2)
Control Variables:							
Software Share	28%	29%	31%	1%	(0.9)	2%	(2.5)
Computer Share	36%	40%	38%	4%	(4.0)	-2%	(-1.6)
Data Skills Share	11%	11%	14%	0%	(0.7)	3%	(5.0)
Cloud Computing Share	0.6%	1.1%	3.0%	0.6%	(7.7)	1.9%	(12.0)
Robotics Share	0.4%	0.6%	1.0%	0.2%	(3.5)	0.5%	(5.5)

TABLE A5: AI Adoption and the Demand for Managers - by Subperiods. The table presents regression results for equation 1, with the dependent variable equal to *Managers Share* in columns (1) and (2); and the natural logarithm of managerial vacancies 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 two subperiods: 2011-2015 (Panel A) and 2016-2022 (Panel B). IV specifications use the instrument described in Section 4. Standard errors clustered at the company level are reported in parentheses.

Panel A: 2011-2015 period

	Managers Share		Ln(Managerial vacancies)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.009	0.022	0.065	0.019
	(0.003)	(0.017)	(0.023)	(0.178)
Observations	4,115	4,115	4,109	4,109
R-squared	0.829		0.960	
F-stat for weak IV		34.29		33.68
Ln(Vacancies) control	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓

Panel B: 2016-2022 period

	Managers Share		Ln(Managerial vacancies)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share	0.001	0.014	0.018	0.092
	(0.001)	(0.007)	(0.007)	(0.056)
Observations	5,761	5,761	5,753	5,753
R-squared	0.853		0.964	
F-stat for weak IV		28.60		28.54
Ln(Vacancies) control	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓

TABLE A6: AI Adoption and the Demand for Managers - Long Differences. The table presents regression results from a long-differences specification, with the dependent variable equal to the change in *Managers Share* (columns (1) and (2)) and the change in the natural logarithm of managerial vacancies (columns (3) and (4)) over the 2011-2022 time period. The independent variable is the change in *AI Share* over the same period; the instrument is also calculated in changes. The sample includes matched Compustat-Lightcast data, with each observation at the company level. Regressions include a control for the change in the overall number of vacancies and 2-digit NAICS fixed effects. Standard errors clustered at the 2-digit NAICS level are reported in parentheses.

	Δ Managers Share		Δ Ln(Managerial vacancies)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δ AI Share (2011-2022)	0.005	0.016	0.043	0.091
	(0.003)	(0.004)	(0.013)	(0.027)
Observations	823	823	820	820
R-squared	0.128		0.710	
F-stat for weak IV		99.53		84.60
Δ Ln(Vacancies) control	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓

TABLE A7: AI Adoption and the Demand for Managers - By Management Category. The table presents regression results with the dependent variable equal to the share of a specific managerial category relative to the total number of managerial vacancies. This analysis aims to determine which types of managers are becoming relatively more important. Each managerial category is defined based on the first three digits of the vacancy's SOC code: "Executives" corresponds to SOC "11-1000", "Marketing and Sales Managers" to SOC "11-2000", "Operations Managers" to SOC "11-3000", and "Other Managers" to SOC "11-9000". The sample includes matched Compustat-Lightcast data in 2011-2022, with each observation at the company-year level. IV specifications use the instrument described in Section 4. Standard errors clustered at the company level are reported in parentheses.

	Executives Share		Marketing/Sales Managers Share		Operations Managers Share		Other Managers Share	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI Share	0.000	0.007	0.004	-0.000	-0.001	-0.004	-0.002	-0.003
	(0.001)	(0.005)	(0.002)	(0.007)	(0.002)	(0.005)	(0.002)	(0.006)
Observations	8,787	8,787	8,787	8,787	8,787	8,787	8,787	8,787
R-squared	0.768		0.773		0.754		0.842	
F-stat for weak IV		93.78		93.78		93.78		93.78
Ln(Vacancies) control	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

TABLE A8: 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, with each observation at the company-year level. IV specifications use the instrument described in Section 4. 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	-0.030	-0.043	-0.042	-0.056	-0.050	-0.077
	(0.017)	(0.049)	(0.017)	(0.049)	(0.017)	(0.050)
Observations	9,876	9,876	9,876	9,876	9,876	9,876
R-squared	0.871		0.870		0.870	
F-stat for weak IV		89.04		89.04		89.04
Firm FE	✓	✓	✓	✓	✓	✓
Industry-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	0.022	0.132	0.011	0.121	0.007	0.097
	(0.019)	(0.080)	(0.019)	(0.080)	(0.019)	(0.078)
Observations	5,761	5,761	5,761	5,761	5,761	5,761
R-squared	0.916		0.916		0.917	
F-stat for weak IV		28.99		28.99		28.99
Firm FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓

TABLE A9: AI Adoption and the Demand for AI Managers. The table presents regression results following equation 1, with the dependent variable equal to *AI Managers Share* in columns (1) and (2), and the natural logarithm of AI-related managerial vacancies in columns (3) and (4). *AI Managers Share* is calculated as the number of AI-related managerial vacancies divided by the total number of a firm's managerial vacancies. The main independent variable is *AI Share*, adjusted to exclude managerial job postings; the instrument is adjusted accordingly. The sample includes matched Compustat-Lightcast data at the company-year level, restricted to firm-years with at least one AI manager. Standard errors clustered at the company level are reported in parentheses.

	AI Managers Share		Ln(AI Managers vacancies)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
AI Share (excl. Mgt vacancies)	0.463	0.969	0.212	-0.060
	(0.067)	(0.241)	(0.035)	(0.221)
Observations	1,483	1,483	1,483	1,483
R-squared	0.754		0.839	
F-stat for weak IV		14.23		14.23
Ln(Vacancies) control	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓

TABLE A10: 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 in at least five managerial and five non-managerial vacancies are included in the regressions. IV specifications use the instrument described in Section 4. 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	0.022	-0.006	0.029	-0.009	0.010
	(0.006)	(0.042)	(0.011)	(0.069)	(0.011)	(0.070)
Observations	4,437	4,437	4,437	4,437	4,432	4,432
R-squared	0.617		0.449		0.418	
F-stat for weak IV		55.51		55.51		55.49
Ln(Vacancies) control	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓