Generative AI Adoption and Higher Order Skills

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We study how Generative AI (GenAI) adoption is reshaping work. While prior studies show that GenAI enhances role-level productivity and task composition, its influence on skills – the fundamental enablers of task execution, and the ultimate basis for employability – is less understood. Using job postings from 378 US public firms that recruited explicitly for GenAI skills (2021–2023), we analyze how GenAI adoption shifts the demand for workers' skills. Our findings reveal that the advertised roles which explicitly rely on GenAI tools such as ChatGPT, Copilot, etc., have 36.7 percent higher requirements for cognitive skills. Further, a difference-in-differences analysis shows that the demand for social skills within GenAI roles increases by 5.2 percent post-ChatGPT launch. These emerging findings indicate the presence of a hierarchy of skills in organizations with GenAI adoption associated with roles that rely on cognitive skills and social skills.

Keywords: Generative AI; Workforce Skills; Technology Adoption

Introduction

Since the release of ChaGPT in November 2022, there has been rapid advancement in the development and adoption of Generative Artificial Intelligence (GenAI) technologies. Adopting these tools has exposed several role types to significant transformation (Bick et al., 2024; Eloundou et al., 2023). Broadly, prior research has identified three ways in which the adoption of new technologies reshapes roles: enhancement, displacement, and reinstatement (Acemoglu & Restrepo, 2018, 2019). Building on this framework, several studies have examined GenAI's impact, showing that it enhances productivity at the role level (Dell'Acqua et al., 2023; Doshi & Hauser, 2024) while both enhancing and displacing tasks required for roles (Handa et al., 2025; Hoffmann et al., 2024). In this paper, we shift the focus beyond roles and tasks to skills – and test for the effects of GenAI adoption in organizations on skills' enhancement and displacement.

Understanding GenAI-driven skill shifts is crucial for three key reasons. First, skills are fundamental to task productivity (Deming, 2017) – and skill-technology interaction shapes task performance. Consider the task of "communicating with supervisors, peers, or subordinates"[1]. Before digital tools like, like email and video conferencing, effective performance required self-management skills (to reach the meeting room on time) and verbal communication skills (to effectively transmit their message). The advent of digital tools likely reduced the need for self-management skills (email reminders worked), amplified the need for digital skills (to use these tools), and shifted focus from verbal to written communication skills (some meetings became emails). Second, focusing solely on task-level enhancement or displacement may misestimate GenAI's impact on employment by overlooking cases where tasks remain unchanged, but the underlying skill requirements evolve. In the example above,

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[1] "Communicating with supervisors, peers, or subordinates" is a standardized work activity (O*NET element id: 4.A.4.a.2) with high average level and importance score across occupations.

"communicating with supervisors, peers, and subordinates" likely remains essential post-GenAI, yet the requisite skills may shift significantly. Lastly, while organizations drive changes at the task and role level, reskilling decisions are often worker-led. This makes skill-level analysis essential for workers navigating their careers and policymakers designing labor market interventions.

In this paper, we take a step towards understanding skill shifts and examine the question: How does GenAI adoption impact the demand for worker skills? To investigate this, we analyze job postings from 378 US public firms who recruited explicitly for GenAI skills from November 2021-November 2023, covering 7.2 million postings and including 6,522 GenAI-related roles. Using keyword-based classification and Deming & Kahn's (2018) skill framework, we measure the skill intensity of advertised roles across ten fundamental skill categories listed in Table 1. In our analyses, we compare skill intensity in roles that use GenAI tools, (henceforth "GenAI roles), to counterfactual roles at different levels of granularity and, subsequently, use a difference-in-differences (DID) approach to track skill shifts post-ChatGPT launch.

Our analyses show that GenAI roles require significantly higher cognitive skills (36.7 percent increase) but significantly lower customer service (53.0 percent), financial (49.2 percent), and self-management skills (58.6 percent) compared to non-GenAI roles. Furthermore, our DID analysis shows that social skill intensity, i.e. the count of associated social skills, increases within GenAI roles post-ChatGPT by 5.2 percent, indicating a shift toward higher collaboration-oriented tasks. These findings align with prior research on technology adoption (Acemoglu & Restrepo, 2018, 2019) and task-level studies (Handa et al., 2025; Hoffmann et al., 2024), indicating that GenAI displaces some skills while enhancing others across and within roles.

Specifically, the results are striking for illustrating two different pathways through which AI may enhance the value of human skills: by being most useful in conjunction with some existing skills (an exposure effect), as well as increasing the demand for some skills in certain roles (i.e., task transformation). That these enhancement effects pertain to "higher order" cognitive and social skills is also noteworthy, because they are possibly harder to automate, as well as form the basis for acquiring new, task-specific skills.

By focusing on skills, this paper contributes to research on the relationship between technology adoption and the nature of work (e.g., Acemoglu & Autor, 2011; Adner et al., 2019; Bloom et al., 2014; Bresnahan et al., 2002; Choudhury et al., 2020). While prior work has examined roles and tasks (e.g., Dell'Acqua et al., 2023; Handa et al., 2025), we focus on higher order skills such as social and cognitive skills that are widely applicable across tasks and roles. Our findings from early GenAI-adopting firms – that GenAI roles are associated with more cognitive skills and increased emphasis on social skills over time – also offer specific insights for workers preparing themselves for a GenAI-augmented work landscape.

Prior Literature

Scholars have extensively examined the question of how technology adoption alters the nature of work (e.g., Acemoglu & Autor, 2011; Adner et al., 2019; Bloom et al., 2014; Bresnahan et al., 2002; Choudhury et al., 2020). Prior research (Acemoglu & Restrepo, 2018, 2019) identifies three broad mechanisms through which technologies impact human work in organizations: enhancement, displacement, and reinstatement. Enhancement occurs when technology amplifies the value added by human work. For example, analytics tools improve analysts' ability to process vast amounts of information, allowing them to generate deeper, more valuable insights. Displacement occurs when technology automates human effort, reducing the need for humans in the process. An example is the launch of ATMs, which increased reliance on self-service banking and reduced the demand for tellers. Reinstatement

happens when automation frees up human effort. The introduction of computer-aided design (CAD) software in engineering and architecture could be seen as an example of this. While CAD automated manual drafting tasks, it allowed designers to shift their focus to higher-level conceptual work and innovation in structural and aesthetic design.

These three mechanisms – enhancement, displacement, and reinstatement – are mutually exclusive and collectively exhaustive, i.e., they describe all possible ways technology influences work. They can also be applied at any level of analysis, whether at the firm, role, task, or skill level.

Building on this framework, several research studies have investigated the impact of GenAI on the nature of work. Existing studies fall into three broad categories. The first set examines the expected exposure of tasks and occupations to GenAI (Bick et al., 2024; Eisfeldt et al., 2023; Eloundou et al., 2023; Felten et al., 2023). One study finds that 20 percent of roles have half of their tasks exposed to GenAI (Eloundou et al., 2023). Another study also finds a positive correlation between high firm GenAI exposure and stock market value post-ChatGPT launch (Eisfeldt et al., 2023). The second set of studies focuses on roles, leveraging field experiments to assess GenAI adoption in roles such as customer service agents (Brynjolfsson et al., 2023), consultants (Dell'Acqua et al., 2023), entrepreneurs (Otis et al., 2023), and writers (Doshi & Hauser, 2024). Their findings indicate that GenAI adoption enhances overall productivity and performance in these professions. The third set of studies analyzes tasks (Handa et al., 2025; Hoffmann et al., 2024) and, using natural experiments and GenAI-human interactions, finds that GenAI adoption results in simultaneous enhancement and displacement of specific tasks within the same individual worker's workflow.

This paper builds upon prior research by shifting the focus beyond roles and tasks to the changes in skills required post-Gen AI adoption. Skills, i.e., developed mental and physical capacities required of roles to perform their tasks (O*NET Online, 2025), are the most granular

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and fundamental building blocks of work (Deming, 2017). Practitioners argue that understanding how GenAI interacts with existing skills and the reskilling it necessitates is crucial for its effective adoption in tasks and roles (Hussin et al., 2024). Prior research supports this intuition. For instance, Deming & Kahn (2018) provide a classification of ten mutually exclusive skill categories that apply across a wide range of roles (presented in Table 1) and demonstrate that having skills in these categories correlates with workers' productivity and pay. Given this background, in this paper, we seek to answer the following question: What is the impact of GenAI on the demand for worker skills? Specifically, we address two sub-questions: (1) How do the skill requirements for GenAI roles differ from other roles? and (2) How do skills for GenAI roles evolve over time?

Data, Sample, and Measures

Our analysis is based on Lightcast job posting data from 378 US public firms between November 2021 and November 2023, covering 7,195,863 job postings. These postings span 513 occupations (at the six-digit Standard Occupational Code level) and 336,217 granular role types identified by Lightcast. The 378 firms in our sample were selected because they posted GenAI-related roles, i.e., roles expected to use GenAI, during this period. Using a keyword-based approach, as often done in previous academic research to measure technology adoption by firms (Alekseeva et al., 2024; Goldfarb et al., 2023; Gulati et al., 2023), we identify 6,522 job postings in November 2022 (launch month of ChatGPT) or after that are indicative of *GenAI Adoption*.

The searched keywords include: "ChatGPT", "Generative AI", "Conversational AI", "LLM", "Large Language Model", "Microsoft Copilot", "GitHub Copilot", "Google Bard", "Google Gemini", "Mistral AI", "Meta LLaMa", "Anthropic Claude", "Perplexity AI", "Grok", "Deepseek", "GPT-3", "GPT-4", and "Prompt Engineer". These postings correspond to 1,437 role types and 157 occupations within our full sample. For our analysis, we define

dummy variables at three levels: *GenAI Role* (1 for the 6,522 identified job postings, 0 otherwise), *GenAI Role Type* (1 for the 1,437 role types, 0 otherwise), and *GenAI Occupation* (1 for the 157 occupations, 0 otherwise). Additionally, we define *Post GenAI*, a dummy variable set to 1 for November 2022 (ChatGPT's launch month) and beyond.

To assess the skills required by roles, we leverage the Lightcast skill taxonomy (Burning Glass Technologies, 2019; Goldfarb et al., 2023). The Lightcast taxonomy consists of approximately 17,000 algorithmically-identified standardized keywords. Each job posting is linked to a subset of these keywords, reflecting its skill requirements. Subsequently, we use Deming & Kahn's (2018) skill categorization in conjunction with the Lightcast taxonomy to measure *Skill Intensity* across ten skill categories. Specifically, we identify Lightcast skills corresponding to Deming & Kahn's (2018) keywords and count their occurrences in each job posting. A higher skill count indicates greater intensity with which the skill is expected to be exercised for that role. Table 1 lists the described skill categories, the associated keywords, and the mean and standard deviation for each category for the job postings in our sample.

Our job posting-based measures – *Skill Intensity* and *GenAI Adoption* – are based on the assumption that job postings reflect role characteristics as they exist within firms. While measurement error is likely in our operationalization, we conduct validation tests to support this assumption. First, we compare the *Skill Intensity* measure to skill-level ratings from O*NET, based on surveys of workers employed in those roles. We find a strong correlation between the two[2], supporting the assumption that job postings-based intensity measure reflects role characteristics. Second, we compare GenAI adoption in job postings with occupation-level adoption measures from other research derived from predictive analysis and worker surveys

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[2] For instance, for social skills, the correlation between the Lightcast measure and the O*NET survey score is 0.711 at the two-digit SOC level and 0.487 at the detailed six-digit SOC level.

and find again a strong correlation[3]. The validation test results are available from the authors on request. Despite their limitations, job postings provide crucial time-varying granular insights into internal organizational characteristics that are unavailable from other data sources.

Analysis and Results

Before analyzing the data to answer our research questions, we examine the occupation groups and industries where GenAI roles have emerged. Figure 1 shows the top five occupations and industries with the highest percentage of GenAI roles. Computer and Mathematical occupations account for the largest share of GenAI roles (43%). Similarly, across firms, Information Technology firms have the highest percentage (25%). This is to be expected as software developers are likely among the first roles required by their firms to use the technology, given its nature. Other research supports this trend, showing that these roles are the most exposed to GenAI, both through predictive analysis (Eloundou et al., 2023) and worker surveys (Bick et al., 2024).

To answer the first question – how does the *Skill Intensity* (across categories) of GenAI roles differ from other roles – we compare GenAI roles against three counterfactual groups, ranked by increasing dissimilarity: (1) other roles within the same role type, (2) other roles within the same occupation (six-digit SOC level), and (3) other roles in other occupations. Our analysis focuses on the period following ChatGPT's launch (November 2022), as GenAI roles are only identified during this timeframe. We employ Ordinary Least Squares (OLS) specification linear regression models with firm and month fixed effects, controlling for total skill count. We cluster standard errors at the firm level.

Figure 2 plots the results of this analysis. We find that cognitive skills (e.g., problem-solving, critical thinking, etc.) are significantly higher in GenAI roles than all three

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[3] The top 5 occupations with the highest GenAI adoption, based on survey data from Bick et al. (2024, Figure 8, p. 20), match the top 5 identified in this paper's job posting analysis (Figure 1a) at the two-digit SOC level.

counterfactual groups. Relative to the sample average (reported in Table 1), GenAI roles exhibit a 36.7 percent higher demand for cognitive skills. Conversely, character (i.e. self-management), financial, and customer service skills are significantly lower in GenAI roles – by 58.6, 49.2, and 53.0 percent, respectively – compared to the three counterfactual groups. These findings align with prior literature on technology adoption (Acemoglu & Restrepo, 2018, 2019) and empirical evidence at the task level (Handa et al., 2025; Hoffmann et al., 2024), suggesting variations in skill enhancement effects of GenAI when comparing *between* roles.

To address the second question – how the *Skill Intensity* of GenAI roles evolves over time – we compare changes in GenAI role types post-ChatGPT launch (November 2022) to the pre-launch period, using other role types within the same occupation (six-digit SOC level) as the counterfactual group. We employ a DID approach, estimating an OLS linear regression model with firm-occupation-role type fixed effects, month fixed effects, and controlling for total skill count. Our primary coefficient of interest is for the interaction term *GenAI Role Type* x *Post-GenAI*. Standard errors are clustered at the firm level. Note that this analysis cannot be conducted at the level of the advertised role, as GenAI roles are only identified post-ChatGPT launch and a DID approach requires a treated group that can be observed both before and after treatment.

Figure 3 presents the results of this analysis. We observe an increase in the intensity with which *social skills* are advertised in *GenAI Role Types* compared to the pre-ChatGPT launch period, adjusting for changes in the counterfactual group. As shown in Figure 3(a), social skill intensity increases by 5.2 percent ($\beta = 0.0281$, $p = 0.005$, sample mean = 0.5391) relative to the pre-launch period. No statistically significant changes are observed for other skill categories. Time-series estimates, calculated for each month in the sample and plotted in Figure 3(b), further illustrate these findings. We find corroboration for the results as we observe that post-launch monthly estimates are significantly higher than zero. Moreover, the pre-launch

estimates are statistically indistinguishable from zero – indicating pre-period parallel trends. These findings support the idea that GenAI role types experience a *within-role-type* enhancement in social skills post-GenAI adoption.

Discussion and Conclusion

In this paper, we examine how GenAI adoption reshapes worker skills, shifting the focus from tasks and roles to the most granular and fundamental unit of work – skills. Our findings indicate that GenAI adoption is associated with significantly higher cognitive skill requirements while reducing the emphasis on customer service, financial, and self-management skills. Additionally, social skills become increasingly prominent within GenAI-related roles over time. Unlike prior studies that focused on task displacement/enhancement (e.g., Handa et al., 2025; Hoffmann et al., 2024) or role augmentation (e.g., Dell'Acqua et al., 2023; Doshi & Hauser, 2024), our skill-level analysis provides novel insights into how GenAI reshapes work within organizations.

Our findings are indicative of the presence of a hierarchy of skills in organizations (Hazan et al., 2024), with GenAI adoption associated with a shift toward higher-order cognitive and social skills. Future research can build on these insights and (1) investigate the emergence of new skills alongside GenAI adoption, which maps to the reinstatement mechanism from Acemoglu & Restrepo (2018, 2019), (2) examine changes in the category of "other skills" beyond Deming & Kahn's (2018) classification, (3) explore how skill shifts aggregate to task and role-level impacts, and (4) analyze how these changes correlate with strategic outcomes such as wages, career progression, and employee turnover. Understanding these dynamics is essential for organizations and workers seeking to navigate the evolving GenAI-augmented work landscape.

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Figures and Tables

Table 1. Summary Statistics: Deming & Kahn (2018) Role Skills

Role skills from Deming and Kahn (2018)	Keywords	Mean	Std Dev.
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics	0.628	0.974
Social	Communication, teamwork, collaboration, negotiation, presentation	0.539	0.757
Character (also referred to as Self-management above)	Organized, detail oriented, multitasking, time management, meeting deadlines, energetic	0.473	0.813
Writing	Writing	0.145	0.376
Customer service	Customer, sales, client, patient	0.955	1.449
Project management	Project management	0.748	1.106
People management	Supervisory, leadership, management (not project), mentoring, staff	0.341	0.711
Financial	Budgeting, accounting, finance, cost	0.236	0.693
Computer (general), Software (specific)	Computer, spreadsheets, common software, Programming language or specialized software	1.748	2.976
TOTAL SKILLS (Skills not covered in the categories above have been coded as Other Skills)		12.799	8.484

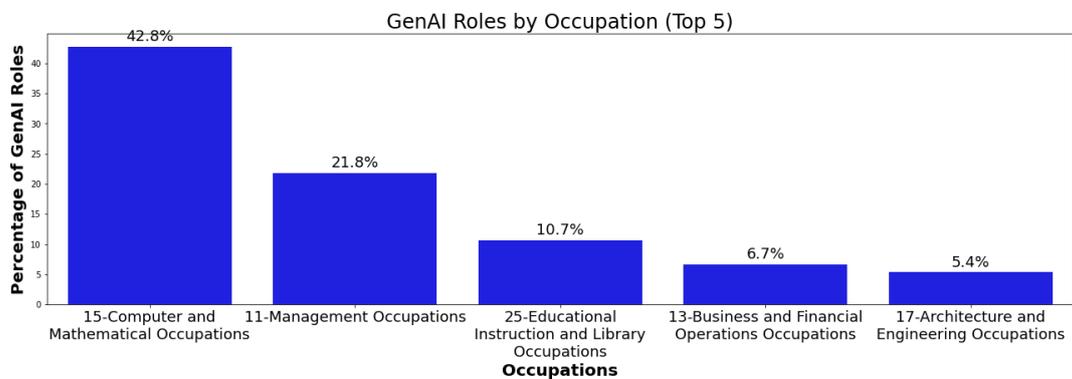**Figure 1.** Descriptive Statistics: GenAI roles by occupation and industry

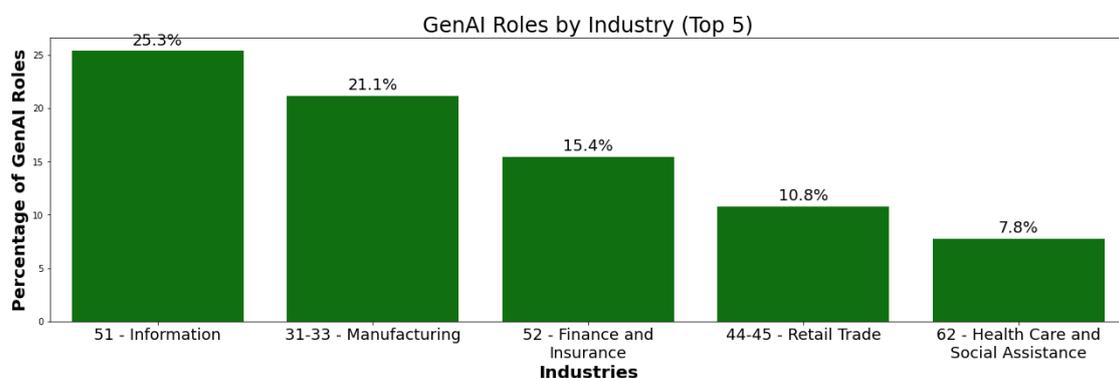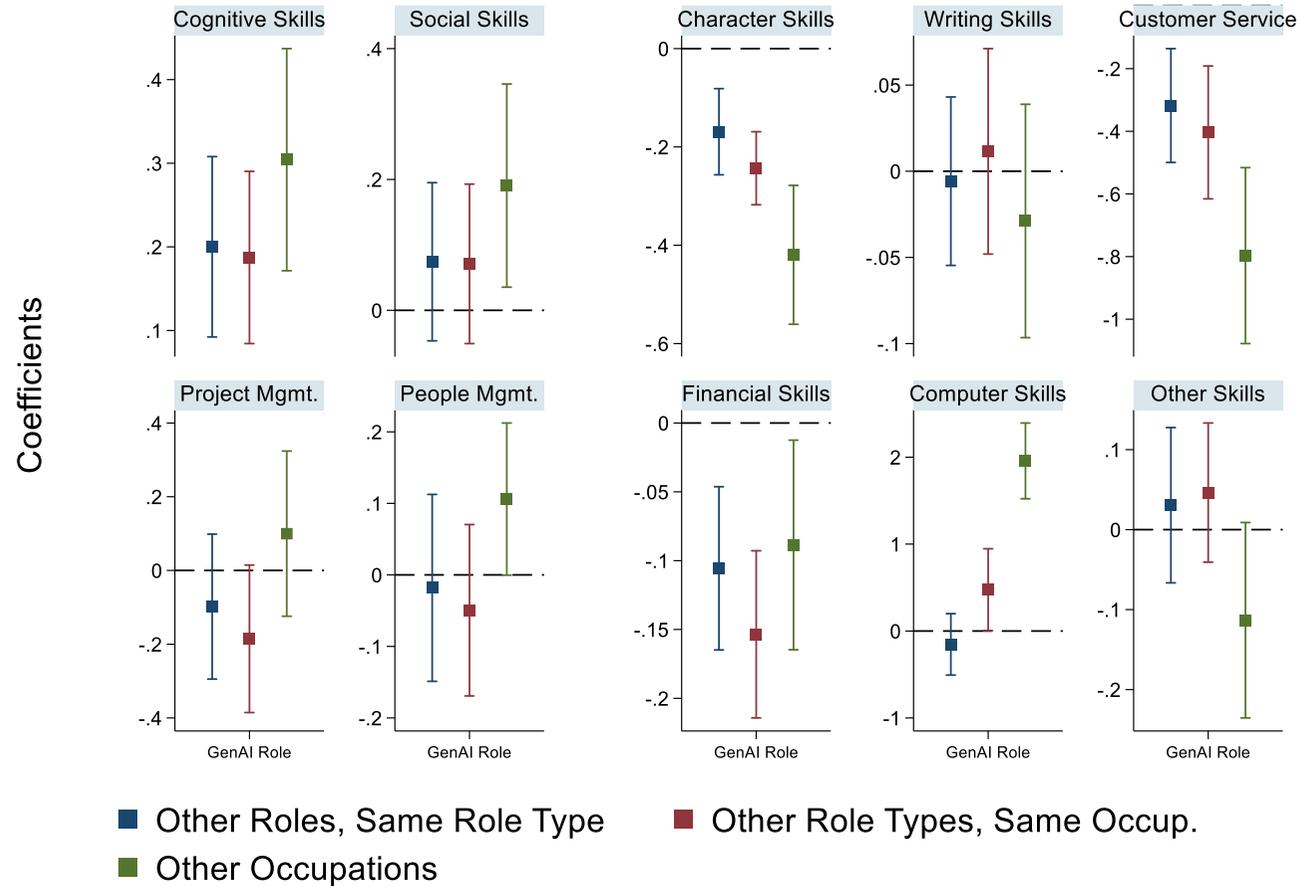Figure 1 (a): GenAI roles by Occupation (Two-digit SOC code)

Figure 1 (b): GenAI roles by Industry (Two-digit NAICS code)

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Figure 2. Between Role Analyses: Comparing *Skill Intensity* for GenAI roles with other roles post ChatGPT launch

Note: The figure above plots the differences in *Skill Intensity* across 10 skill categories identified in Deming & Kahn (2018) when comparing *GenAI Roles* with (1) other roles within the same role type (GenAI Role = 0, GenAI Role Type = 1), (2) other role types within the same occupation (Gen AI Role = 0, Gen AI Occupation = 1), and (3) other occupations (Gen AI Role = 0, Gen AI Occupation = 0). Coefficients for the dummy variable *GenAI Role* from Ordinary Least Squares (OLS) specification linear regression models with firm and month fixed effects and controls for total skill count have been plotted. Standard errors are clustered at the firm level. 95% confidence intervals have been shown.

Figure 3. Within Role Type Analyses: Comparing *Skill Intensity* for GenAI role types, pre and post ChatGPT launch, with other role types.
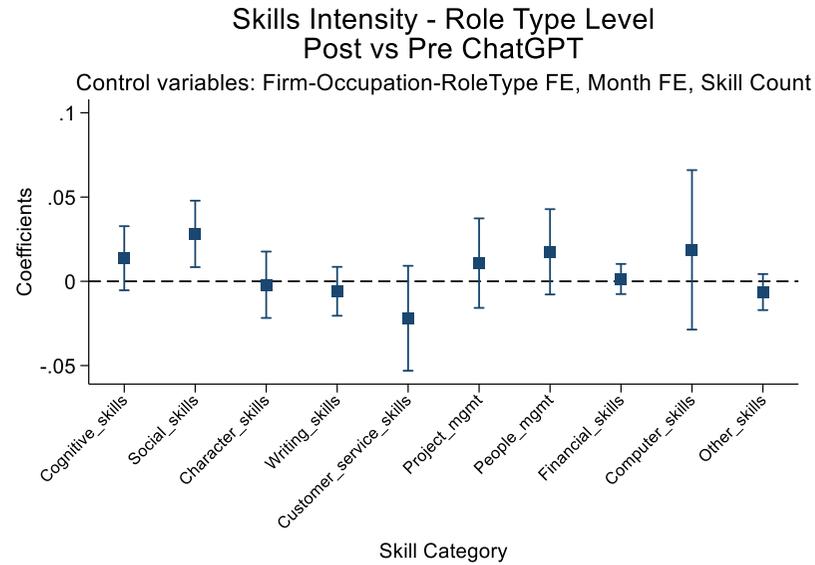

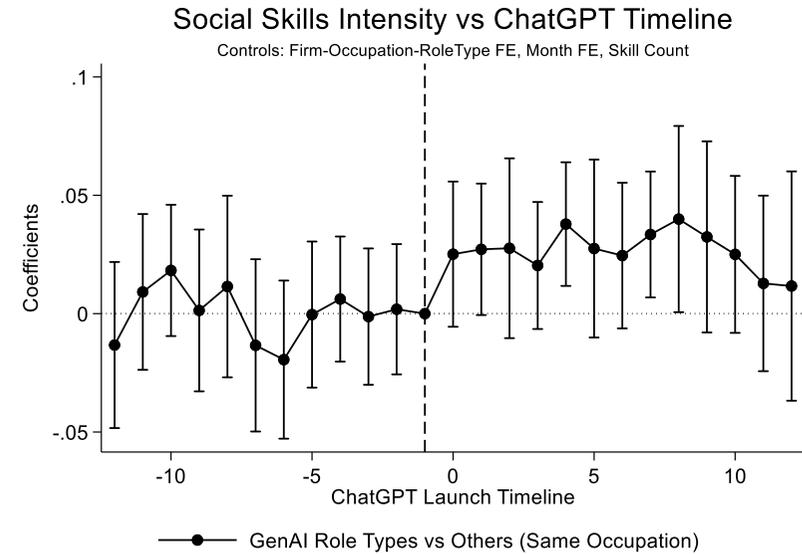Figure 3 (a): Changes in Skill Intensity for GenAI role types over time

Figure 3 (b): Time Series Estimates for Social Skills

Note: Figure 3(a) plots the changes in *Skill Intensity* post ChatGPT launch (November 2022) across the 10 skill categories identified in Deming & Kahn (2018) when compared to pre-ChatGPT launch. Other role types within the same occupation (six-digit SOC level) have been used as the counterfactual group. Coefficients for the interaction term *GenAI Role Type X Post-GenAI* from a difference-in-differences (DID) OLS linear regression model with firm-occupation-role type fixed effects, month fixed effects, and controlling for total skill count have been plotted. Figure 3(b) plots the time series estimates for the coefficients for the terms *GenAI Role Type X Month* (October 2022, one month before ChatGPT launch is the base month) from models that are otherwise similar to those plotted in Figure 3(a) for *Social Skills* – the skill category for which we observe a statistically significant coefficient in Figure 3(a). Standard errors are clustered at the firm level. 95% confidence intervals have been shown.