Organizational Technology Ladders: Remote Work and Generative AI Adoption

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Abstract

In this study, I propose a novel link between two of the biggest technology shocks to firms in the last decade: remote work and generative AI. I develop a model of firm investments in new technology that shows how first adopting remote work can make it easier for a firm to adopt generative AI, and how generative AI adoption in turn may reduce remote hiring. I test these predictions using detailed job posting data. I develop an IV approach to estimate the causal effect of remote work on firms' adoption of generative AI technologies and find large positive effects of remote work on generative AI skill demand. Conversely, I provide evidence from a synthetic difference-in-differences approach that firms that were more exposed to generative AI technology reduced their demand for remote workers after ChatGPT was released. Moreover, I provide evidence for the mechanism through which this "organizational technology ladder" operates: remote work adoption changes the characteristics of a firm's workforce in a way that makes it easier to adopt generative AI. When firms go remote, they upskill their workforce and hire more workers with decision-making skills and technology skills. These characteristics in turn enable more rapid generative AI adoption. In contrast, firms with many jobs that require interaction and communication are less able to substitute generative AI for remote workers.

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"As a general rule, it now looks like AI may be able to replace human labour in many virtual settings, meaning that if a task can be done remotely, it can also be potentially automated."
Frey and Osborne (2024)

"The big way to protect yourself [from AI] as an individual is be in a role that requires some in-person interaction, even if that's every other month...To meet co-workers, manage, or mentor every other month creates an activity that AI cannot do."
Nick Bloom (Business Insider, 2023)

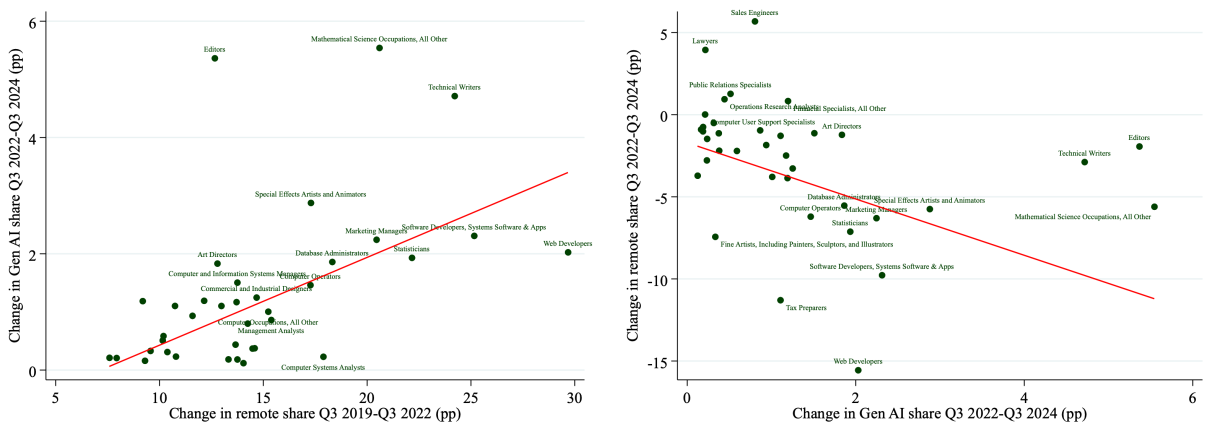
Since 2020, the Covid pandemic tested the resilience of cities, companies and society at large, and led to broad shifts in social preferences and the organization of work (Glaeser and Cutler, 2022). An important consequence for firms was the rapid rise in remote work from a rare occurrence to about 28% of all workdays being worked from home by 2023 (Barrero, Bloom, and Davis, 2023), which can be thought of as a change in "organizational technology" that required firms to change the way they manage and interact with their workers. Less than three years after the onset of the pandemic, the release of ChatGPT in November 2022, and the subsequent rapid improvements in generative AI technology are propelling another shock to organizations. Generative AI has the potential to increase productivity in a large share of tasks across occupations (Eloundou, Manning, Mishkin, and Rock, 2023), and field experiments have found large productivity increases when workers are given access to generative AI-based tools (Noy and Zhang, 2023; Brynjolfsson, Li, and Raymond, 2023).

As a result, firms have adopted the new technology at an unprecedented pace compared to previous technology waves Bick, Blandin, and Deming (2024). Given the potential firm productivity impacts and labor market consequences of widespread automation of the tasks to which generative AI tools can be applied, it is important to understand why some firms are more likely to scale up the use of generative AI tools and how this reshapes the organizational structure of firms.

In this study, I show how these large technology shocks—remote work and generative AI—reshape firms' organization in terms of skill demand and hiring for different roles. One of the key insights is that these technology waves are not separate phenomena: firms build on, and transform in response to, one technology adoption, which then creates path dependence for the costs and benefits of adopting the next technology—that is, there is an "organizational technology ladder" through which remote work and generative AI adoption are linked. To be specific, this analysis builds on two novel empirical facts, which are shown in Figure 1: among occupations where firms substantially increased remote work, those that adopted remote work at a faster rate from 2019 to 2022 were much more likely to also ramp up hiring for generative AI-related skills from 2022-2024 after ChatGPT was released

Figure 1:
Changes in remote work and generative AI adoption

These figures focus on the top quartile of remote work adopting occupations (based on 2021/2022 job postings). Panel A shows the change in hiring for generative AI skills after the release of ChatGPT (Q3 2022-Q3 2024) as a function of remote work changes during the pandemic (Q3 2019-Q3 2022). Panel B shows remote work changes after the ChatGPT release as a function of generative AI adoption over the same period. Both graphs only include occupations with > 1K job postings in Q3 2022 with some Q3 2024 Gen AI adoption (> 0.1% of jobs). Two outlier occupations, 'Computer Programmers' and 'Writers & Authors' are not included for better visibility, but follow similar patterns. The data are Lightcast job postings where "Gen AI adoption" is the share of jobs mentioning Gen. AI-related keywords.



(A) Δ Remote Work ('19-'22) and Gen. AI adoption ('22-'24)

(B) Gen. AI adoption ('22-'24) and Δ Remote Work ('22-'24)

(panel A). However, in the same occupations where firms increased hiring for generative AI skills, the share of hiring for remote jobs then declined after ChatGPT was released (panel B).

In this paper, I provide both a conceptual framework and causal empirical evidence that suggests that this relation between remote work and generative AI adoption can be explained by a mechanism where organizational changes resulting from remote work adoption make it easier to adopt generative AI. Conversely, changes in organizations in response to generative AI cause firms to reduce remote hiring. As a result, remote work and generative AI are intimately connected in their effect on firms and workers.

To motivate the idea that remote work and generative AI are linked, I first provide new descriptive evidence that these technologies are likely to affect one another at the level of firms and occupations. I document the following facts: (1) When looking at time series, generative AI adoption rates are higher and rising more steeply among occupations that are more remote. (2) The rapid rise in remote work that began with the Covid pandemic reversed exactly at the point in time when ChatGPT was released and the reversal was greatest among occupations that adopted generative AI at a higher rate. (3) The same firms and industries that have a high remote work prevalence are also adopting generative AI at a higher rate. (4) Occupations with tasks that are highly amenable to remote work also have high exposure to generative AI productivity improvements. These facts show that there is large potential for the two technologies to compound or mitigate one another's effects. Moreover, the time pattern is suggestive of both remote work complementing the adoption of generative AI, and generative AI adoption substituting for remote work demand.

Second, I develop a conceptual framework that captures the potential channels for *why* remote work and generative AI technology adoption are connected. This model builds on two key ideas: (i) each firm divides workers' total time between routine production and decision-making, and the production boost from better decision-making depends both on the worker's own time investment and on the decision support from managers at the firm; (ii) The tasks that are still done by the worker, after automating some tasks with generative AI, tend to be more sensitive to the quality of decision-making. I show that these basic assumptions allow me to derive predictions for the relation between remote work adoption and subsequent generative AI adoption, as well as for how remote work prevalence should evolve in response to investment in generative AI.

In this model I represent the effect of remote work as an increase in productivity by the worker, albeit at the cost of lower decision-making quality. Generative AI, in contrast, is an automation technology that reduces the tasks done by the worker, but is more likely to leave tasks to the human that benefit from good decision-making. This model allows different firms to have different fundamental suitabilities for adopting either of these technologies, as some types of jobs benefit more from remote work than others, and some have greater generative AI automation potential. Moreover, it captures the idea of of technologies that build on one another: the costs of adopting each technology depend on current levels of information technology at the firm, such that investment in remote work tools also lowers the incremental investment needed to implement generative AI. As long as these complementarities in infrastructure are large enough, remote work adoption always makes generative AI use more likely. At the same time, generative AI adoption makes the output from workers' remaining tasks more reliant on good decision-making. This reduces firm incentives to allow remote work, as the lower ability to make good decisions with the help of firm management when working from home becomes costlier. In short, the tasks that remain for humans to do after AI automation need more guidance from others, and thus benefit more from being done in person. In addition to being able to explain the empirical facts shown in Figure 1, the model also generates new predictions that both remote work adoption and generative AI adoption should result in higher levels of hiring for technology skills and for decision-making skills.

Third, the main part of the paper tests these predictions and provides empirical estimates of the causal effects of a higher rate of remote work at a firm on its adoption of generative AI, and the causal effect of generative AI adoption on remote work hiring. To test whether the effect of remote work on generative AI adoption is causal, I develop an IV strategy based on firms' exposure to labor market competition from *other firms* that are more likely be offering remote work as a benefit for their workers, interacting with a firm's own ability to offer such a perk. I find that a 10 pp higher remote work share causes firms to increase their hiring for generative AI skills by at least 0.8 pp by 2024. These effects are robust to controlling for a flexible set of control variables that capture firms' fundamental suitability for remote work and generative AI automation. When allowing for heterogeneity in these effects, I find that firms with a greater emphasis on communication-intensive roles and decision-making are less likely to adopt generative AI in response to remote work, while firms that previously hired for more technology skills show stronger "technology ladder" effects.

Fourth, I find that remote work adoption during the pandemic reshapes organizations as it causes firms to "upskill", increasing demand for higher-skilled occupations and college-educated workers, and also increases hiring for roles that are associated with higher decision-making intensity, leadership skills, and managerial responsibility. At the same time, remote work adoption causes firms to increase their investment in technology skills, such as data management and machine learning, and to hire more for computer occupations.

Fifth, I use a synthetic difference-in-differences design following Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021) to estimate the effect of being a firm with high (top decile) generative AI automation potential on firm hiring characteristics around the event of the ChatGPT release, compared to firms with comparable remote work trends before the release. I first document that greater generative AI exposure was indeed associated with higher subsequent adoption of generative AI, particularly in firms where roles are more decision-making intensive, where workers are more experienced, and where workers have more technology skills. Note that these are exactly the kinds of roles for which firms that adopt remote work increase their hiring. This provides a mechanism for one of my key findings: high generative AI exposure causes firms to reduce their remote hiring after the ChatGPT release. In line with the pattern in the raw data, greater exposure to generative AI led to a reduction in remote hiring by about 19% for the most exposed (top decile) firms relative to a synthetic control group with similar remote work trends before the release, but with lower generative AI exposure.

These results suggest the existence of what I call an "organizational technology ladder": firms that adopt one technology—remote work in this case—then benefit more from subsequent technology waves—generative AI—that build on the same investments in skills and requires similar changes in work processes. The results on changes in skill demand suggest that this mechanism operates through the way that remote work induces firms to increase their level of technology skill, and shifts their hiring towards more experienced workers in decision-making intensive roles. In turn, these characteristics increase their ability to benefit from the adoption of generative AI tools. This path dependency can further exacerbate differences in productivity among firms and labor market outcomes among workers that result from the two biggest technological changes in firms' work processes during the last decade.

Related Literature. This paper builds on, and aims to link, two growing, but separate, literatures on the effects of remote work and generative AI on firms. For an overview of the remote work literature, see, e.g. Barrero et al. (2023), while an early review of the emerging evidence regarding firm-level effects of generative AI can be found in Eisfeldt and Schubert (2024). While this paper is, to my knowledge, the first study to draw a link between remote work and generative AI adoption, previous studies have found that information and communication technology investments may complement work-from-home productivity: Boeri, Crescenzi, and Rigo (2024) show that, while the overall effect of work-from-home on productivity was negative for firms in Italy, this effect was less negative for larger firms, those that had previously invested in laptops and server setups before the pandemic, and for knowledge-intensive firms. Also, in line with the findings in this paper, some studies have found that one of the reasons why remote work benefits from existing investments in communication technology may be that remote work creates more communication overhead (Bao, Li, Xia, Zhu, Li, and Yang, 2022; Gibbs, Mengel, and Siemroth, 2023).

My finding that greater remote work may be associated with a greater investment in potentially automating technologies also relates to a literature that finds that remote work changes the attachment between firms and their employees: Akan, Barrero, Bloom, Bowen, Buckman, Davis, Pardue, and Wilkie (2024) show that remote employees tend to live farther away from their employment locations, and that they are both more likely to be fired when companies contract and to be hired when companies expand. Moreover, remote employees require more time spent on coordination activities and meetings, but also receive less time in personal or small group meetings with their manager (Gibbs et al., 2023), which suggests that the *quality* of employee engagement with co-workers declines for remote workers. As a result, remote workers may have a lower chance of being promoted. For example, Emanuel and Harrington (2024) show that remote call center employees had substantially lower chances to be promoted before the pandemic than on-site employees.

Moreover, my IV estimation approach relies on the argument that work-from-home is a workplace amenity that matters for labor market competition among employers. There is now a growing literature that shows that work-from-home is considered equivalent to a sizeable wage increase for workers in terms of the attractiveness of a job. Maestas, Mullen, Powell, Von Wachter, and Wenger (2023) find that the opportunity to telecommute is equivalent to a 4.1% wage increase for workers. Similarly, Powell and Wenger (2024) show that hiring managers consider providing opportunities to work from home as equivalent to a 9.4% wage increase for their workers. Other studies have found that offering hybrid work options increases worker retention (Bloom, Han, and Liang, 2024), and that remote workers are more productive as a result of shorter commmute times and better work-life balance (Choudhury, Foroughi, and Larson, 2024). Nonetheless,there has recently been a pushback by some companies against the prevalence of remote work, with several large firms announcing "return-to-office" policies.[1] While I do not focus directly on why firms might want their workers to return to in-person work, the reduction of remote hiring in response to the adoption of generative AI that I document is consistent with firms looking for alternatives to remote work.

With regard to broader effects on the economy, the results in this paper have important implications for the geographic disparities in the impact of the technology shocks of interest: The Covid pandemic and the resulting remote work adoption substantially reshaped the urban landscape by triggering an exodus of city dwellers to the suburbs (Gupta, Mittal, Peeters, and Van Nieuwerburgh, 2022a). As a result, residential housing demand increased and drove a large run-up in house prices (Mondragon and Wieland, 2022; Davis, Ghent, and Gregory, 2024), while commercial office real estate in many downtown areas is reeling from the decline in demand for physical office space (Gupta, Mittal, and Van Nieuwerburgh, 2022b). Whether the generative AI technology wave reinforces or mitigates the adoption of remote work, and whether the effects coincide in the same workers, firms, and cities, is therefore of great importance for whether cities and real estate markets will be able to recover from the remote work technology shock.

This paper has the following structure: the next section discusses the data that I use. Section II discusses a set of new stylized facts regarding the relation between remote work and generative AI. In Section III, I provide a simple conceptual framework for how remote work and generative AI might interact from the perspective of a firm, which guides the empirical approach to estimating the causal effects of remote work adoption that is presented in Section IV. Then, I first estimate the causal effect of remote work on firm-level skill demand in Section V, and then on generative AI adoption in Section V.C. I reverse the direction

[1] For example, Starbucks: https://www.wsj.com/business/starbucks-tells-workers-to-return-to-the-office-or-mod=itp_wsj

of analysis by estimating the effect of generative AI adoption on remote work prevalence in Section VI. Finally, Section VII draws out the implications of these results in a discussion of how the concept of an "organizational technology ladder" relates to the evidence in the case of remote work and generative AI.

I. Data

Occupational wage and employment data. I obtain data on employment and average wages by occupation and MSA from the Bureau of Labor Statistics Occupational Employment Statistics. I cross-walk all occupational data to SOC 2010 codes and crosswalk New England City and Town Areas (NECTAs) into Core-Based Statistical Area codes for the few geographies where the OES data is not provided at the level of CBSAs.

Job postings. Both hiring activity and investments in Generative AI skills and other characteristics of new jobs are measured using job postings data from Lightcast. This data consists of the near-universe of online job postings in the U.S. from Jan. 2010 to Oct. 2024. I filter job postings in the following way: (1) Drop job postings by staffing companies. (2) Drop all jobs flagged as internships. (2) Retain only full-time jobs, dropping part-time jobs. Moreover, I create variables that represent particular key characteristics based on the job postings data: most importantly, the classification of *remote* jobs used in most of the analyses below represents jobs that indicate that the position is fully remote. However, some jobs may allow only for hybrid remote working, so, where applicable, I will explicitly note where *hybrid remote* jobs are included. I also create dummy variables for the minimum level of required education distinguishing whether a high school, Associate, Bachelor, Master, or Ph.D. degree are required. Similarly, I create dummies for different required experience levels in years. When job postings are aggregated into firm or occcupation or firm-by-occupation level panels, the counts reflect the number of job postings *posted* in each category in the time period, which does not necessarily reflect actual hiring, but rather proxies for hiring demand.

Generative AI adoption. While I cannot observe the *usage* of Generative AI within firms, the job posting data allows me to see when firms are either requiring Generative AI-related skills from new workers, or describing the work activities in a job as involving Generative AI tools. Therefore, I will use mentions of Generative AI and related technologies in job postings as a proxy for the degree to which those jobs involve using Generative AI-related tools. Labels for "Generative AI" skills mentioned in a job posting are supplied by Lightcast based on the job posting text.

Occupation characteristics. To evaluate whether the estimated effects differ between occupations with different characteristics, I use O*Net data on the characteristics of different occupations to construct summary measures that assess the prevalence of different skills in different occupations. I construct the following measures of occupation characteristics: Whether a job requires extensive preparation in the form of training, experience, or degrees is captured by the O*Net measure of "job zones", where a higher job zone can be used as a proxy for a job that is less "routine" (Kogan, Papanikolaou, Schmidt, and Seegmiller, 2023). I assign an occupation to the "high job zone" group if it is at least in job zone 4 ("considerable preparation"). To capture the importance of "decision-making" in a job, I average the level of different work activities involved in an occupation according to O*Net, based on Deming (2021), and define the "high" group as the top quintile.[2] Indicators of coordination required, interaction, social skills and social skills interacted with analytical skills are constructed as described in Deming (2017). I construct a measure of job inflexibility based on Goldin (2014), a measure of leadership skills based on Schubert, Stansbury, and Taska (2019).

II. Stylized facts: remote work and generative AI

To understand whether firms are more or less likely to change their investments in hiring for generative AI skills if they already have a remote workforce, or might change their remote hiring with the emergence of generative AI tools, I start by providing descriptive evidence that these two technologies are likely to be connected. In this section, I document a number of novel facts about remote work and generative AI skill demand. The next section will then provide a conceptual framework for a causal link between the adoption of these two technologies and later sections estimate the magnitude of the causal effect.

A. Remote work and generative AI prevalence by occupation

To provide some intuition for which occupations are adopting the technologies of interest, Table I ranks 6-digit occupations by their prevalence of remote jobs (panel A) and generative AI (panel B) in job postings, as of YTD Sep. 2024. Each table shows the top 20 occupations for one technology that have at least 5,000 job postings in the sample.

The lists show that remote work is highly prevalent among occupations that vary substantially in the degree of social interactions and education required, including Actuaries, Telemarketers, and Mental Health Counselors, for example. High Generative AI adoption is more prevalent among technical or writing-heavy occupations, but also includes a num-

[2]These activities are: Making decisions and solving problems; Developing objectives and strategies; Organizing, Planning and prioritizing work.

ber of teaching occupations, as well as Marketing Managers. In panel C, I explore whether the list of top generative AI adopters looks different *conditional* on being a remote worker (including only occupations with at least 100 remote job postings). Notably, many of the top adopters in general are also heavily featuring generative AI in remote job postings—there is substantial overlap between the lists—but the adoption rates among remote workers are substantially larger. For example, Technical Writer job postings mention generative AI in 6.1 percent of all job postings, but in 18 percent of remote job postings.

Fact 1: *The occupations that adopt generative AI at high rates are similar between remote and non-remote workers, but generative AI adoption rates are higher among remote workers.*

B. Trends in generative AI adoption

How has the adoption of generative AI and remote work changed over time? Both of these technologies experienced a key time period that accelerated their adoption: for remote work, the onset of the Covid pandemic in Q1 2022 played an important role as many positions went remote during the first year of the pandemic. For generative AI, the release of ChatGPT in November 2022 launched the technology into public awareness and demonstrated many potential use cases.

Figure 2 shows how adoption rates of both technologies have varied over time: panel A shows that generative AI adoption surged after ChatGPT was released, with 0.3-0.4% of all job postings mentioning the technology on average, or 21K jobs per quarter as of Q3 2024. Importantly, this generative AI adoption rate has been much higher in occupations that have high rates of remote work prevalence. The occupations in the highest quartile of remote work adoption have generative AI adoption rates around 4 times the national average.

Panel B of Figure 2 shows that the remote work share in job postings experienced a surge starting in Q2 2020, and continued to rise after that, all the way *until ChatGPT was released*. After Q4 2022, remote work jobs started to decline again. While it is possible that this is a coincidence, the timing strongly suggests that generative AI adoption played a role in halting the rise of remote work. This becomes even more evident when considering the time pattern disaggregated by ex post adoption rates for generative AI as of YTD Sep. 2024: the drop in remote work shares is particularly pronounced for the occupations that saw the highest generative AI adoption, more moderate for the second-highest quartile, and not visible at all for occupations with below-median generative AI use. As far as I know, this fact pattern reveals a a novel fact:

Fact 2: *The rise of remote work reversed exactly when ChatGPT was released, and this reversal was greatest in occupations that ended up adopting generative AI at a higher rate.*

These trends suggest that there is a strong link between generative AI adoption and the time trends in remote work. Moreover, they suggest that the causality of the link can run in both directions, with remote occupations being more likely to adopt generative AI tools, while generative AI use also impacted the use of remote workers. The following sections will try to disentangle what explains this relationship between the technologies.

C. Firm-level correlation between remote work and generative AI

Does the relationship between occupational remote work adoption and generative AI use also exist at the firm level? The occupational trends do not necessarily imply that the two technologies should be positively correlated in their prevalence at the firm level. For instance, if they represent different solutions to a similar organizational problem but involve some fixed costs or are not compatible with one another, firms might choose to deploy one or the other, but rarely both. In that case, a positive correlation at the occupation-level could coincide with a negative correlation at the firm level.

I aggregate the job postings data to both the level of companies and 2-digit industry sectors. The correlations at these levels between the log of the remote share of job postings and the log of the share of job postings mentioning generative AI are shown in Figure 3. The relation is positive both at the industry sector level (panel A) and at the firm level (panel B), with the log of the remote share explaining 43% and 13% of the log generative AI adoption rate at the industry and firm level. While these correlations are not necessarily causal (see the empirical approach detailed below), they suggest that they tend to occur in the same industries and firms, such that managers in the affected areas of the economy are likely to either be integrating both technologies into their firm, or neither.

Fact 3: *The same firms and industries that have a high remote work prevalence are also adopting generative AI at a higher rate.*

The next section provides a conceptual framework for how these technologies may be linked.

III. Conceptual framework: organizational technology ladders

Why would having many workers in remote positions *cause* a firm to adopt generative AI at a faster rate? In this section, I provide a conceptual framework for how remote work and generative AI adoption can be linked that is based on a firm's decision to invest in different technologies, which can then have effects on the ability, and cost, of investing in another technology. That is, from an organizational management point of view, one technology might represent a "ladder" to adopting another technology, which introduces path dependence into firm investment choices, and interdependence between the technologies in their impact on firms, workers, and the broader economy.

The effects of remote work on generative AI adoption are potentially ambiguous: generative AI tools could complement remote workers more than in-office workers if they can build on their existing familiarity with digital workflows to lead in using tools like LLM-based chat bots productively. However, those same digital workflows and the associated data about processes and work products also make it easier to develop and fine-tune models to automate remote workers' tasks. At the same time, firms that have experience in adapting their organization to remote operations may have greater organizational and technical capabilities to deploy cutting-edge generative AI models. If there is a fixed cost involved in such retooling, and remote work already unlocked some of the productivity benefits of decentralized production (e.g. through the lower labor costs of personnel in cheaper labor markets), it is also possible that existing remote work infrastructure obviates the need for additional generative AI investments. It is therefore an empirical question whether a greater use of remote workers is likely to lead to more or less generative AI investment by firms, and how this impacts a firm's demand for different roles in its remote and in-office workforce

Moreover, a suitable model to interpret the empirical results needs to account for a number of different channels through which remote work might be linked to Generative AI adoption:

1. *Augmentation:* Remote work jobs might benefit directly from applying generative AI tools, and this greater benefit of adoption drives higher demand for generative AI skills.

2. *Common infrastructure:* the digital capabilities, data processing capacity, and other technical capacity improvements that result from implementing a remote work-friendly organization, may make it easier to adopt generative AI technologies.

3. *Task characteristics:* the nature of the tasks that are amenable to being done remotely also happens to make generative AI useful in them, such that generative AI exposure and exposure to being done remotely coincide in the same jobs and firms, but without a causal link between them.

4. *Tech-savvy:* some firms may have organizational cultures and leadership that are more open to embracing new technologies and being at the leading edge of innovation. This trait may make these firm more likely to experiment with, and adopt, both remote work and generative AI as the newest waves of technological progress.

Below, I develop a parsimonious model of the firm choice of investment in technology, and of changes in organizational structure in the form of remote work adoption and the choice of the optimal decision intensity of work. This framework captures all of the mechanisms listed above. The model builds on two key ideas: (i) the firm divides workers' total time between routine production and decision-making, which adjusts in response to the availability of support from managers at the firm and the degree to which an occupation benefits from better decision-making; (ii) The tasks that are still done by the worker after automating some tasks with generative AI tend to be more sensitive to the quality of decision-making. I show that these basic assumptions allow me to derive predictions for the relation between remote work adoption and subsequent generative AI adoption, as well as how remote work prevalence should evolve in response to investment in generative AI.

A. *Occupational output*

For simplicity, assume that each firm consists only of one production occupation (which we can relax in a quantitative estimation of this model). A worker in occupation j, which, in this simplified framework also indexes the type of firm that employs the worker, at firm f, produces output y_{fj} given by the following expression:

$$\ln y_{fj} = k_{fj} + \int_{k_{fj}}^{j} \ln\left(\frac{1-D_f}{j-k_{fj}}\right) dx + \int_{k_{fj}}^{j} \delta(x) Q_{fj} dx + \int_{k_{fj}}^{j} r_j \times \mathbb{1}[\text{Remote}_f] dx \quad (1)$$

Here, the automated product $k_{fj} < j$ represents how much of the task spectrum $[0, j]$ is automated (or does not require labor) at firm f. The integral $\int_{k_j}^{j}$ can be seen as a stylized representation of the "remaining tasks" from k_j to j that must be performed by labor. D_f is the time spent on making independent decisions by workers at firm f rather than producing output.

The term $\delta(x)$ captures the importance of decision-making for tasks of different complexity that the worker does. Importantly, I assume that $\delta'(x) > 0$, i.e. when we sort tasks by automatability, less automatable tasks tend to benefit more from good decisionmaking by the worker. For tractability, I will assume $\delta(x) = e^x$.

Q_{if} is the decision quality which represents the productivity "boost" from good decision-making. Decision quality is defined as

$$\mathrm{Q}_{if} = \ln\left[\underbrace{\eta D_f}_{\text{Worker input}} + \underbrace{\rho^{\mathbb{1}[\text{Remote}]} M_f}_{\text{Firm input}}\right],$$

where M_f is the quality of decision support from the firm (e.g. from better central management), and $\rho < 1$ is the discount factor in decision support due to remote work barriers to communication.

The last term in equation 1 represents the productivity benefit of working remotely, which may differ by occupation. This allows for some occupations where working from home is easily accomplished and productive, while in other occupations it may either be physically infeasible (e.g. for an emergency room nurse) or undesirable for other reasons.

B. *Optimal decision-making intensity*

We will work backwards to derive the firm's optimal choices for technology investment. After a firm chooses whether to adopt a technology, it determines the efficient amount of time for its workers to spend on decision-making. There is a trade-off, as time spent on decisions D_f is time spent not producing task output, so spending more time on decisions will only be optimal for firms that have tasks are sensitive to good decision-making, i.e. where $\delta(x)$ is high on average.

Maximizing the expression in equation 1 with regard to D_f, the optimal decision intensity is

$$D_f^* = \frac{(e^j - e^{k_{fj}}) - \frac{1}{\eta}(j - k_{fj})\rho^{\mathbb{1}[\text{Remote}]} M_f}{(e^j - e^{k_{fj}}) + (j - k_{fj})}. \tag{2}$$

This expression directly implies that local decision intensity is higher in: (1) firms where local worker decisions are more important (higher η); (2) firms where management decision support is worse (lower M_f); (3) firms that work remotely ($\rho^{\mathbb{1}[\text{Remote}]} < 1$).

Remote work and decision quality. Firms that work remotely invest more worker time to make good decisions in order to undo the reduction in central decision support due to communication issues. What does this mean for the overall decision quality in remote firms, all else equal? In Appendix B, I show that an increase in central decision support is not going to be fully offset by a reduction in local decision intensity. This implies that *remote firms have lower overall decision quality even though they invest more worker effort in local decision-making*. That is, $D_f^R > D_f^{NR}$ and $Q_f^R < Q_f^{NR}$, where R and NR denote optimal choices conditional on going remote or staying non-remote.

C. Technology adoption

Taking into account the optimal allocation of worker time to decisionmaking, the firm decides in an earlier period t whether to adopt a new technology τ. I assume that the firm does not anticipate future technology waves, so each technology investment decision is made without anticipating the next one.

Technology implementation costs. Each new technology τ that the firm adopts—where, for concreteness, $\tau \in \{\text{Remote}, \text{GenAI}\}$—requires a level of ICT capital I_τ, which has cost

$$c_f^{\tau_t} = \frac{1}{T_f}(I_{\tau_{f,t}} - I_{\tau_{f,t-1}})^2,$$

where T_f is a measure of the firm's "tech-savvy", which reduces its investment costs, and $\tau_{f,t}$ and $\tau_{f,t-1}$ represent the current technology being considered for adoption, and the last technology actually adopted by firm f. That is, new investment is costlier if the firm did not adopt previous technologies, such that there is a bigger gap between the firm's level of technology infrastructure and the level required for the current technology.

Optimal technology adoption. Each firm adopts a new technology if the benefits of doing so outweigh the benefits *or* if the firm is forced to do so by policy, for example, having to adopt remote work as a result of pandemic lockdowns. Generally, the firm adopts new technologies if the increase in output is greater than the cost of adopting the technology, i.e.

$$\ln y_{fj}^{\tau_t} - \ln y_{fj}^{\tau_{t-1}} > c_f^{\tau_t}.$$

Note that a firm of a given type j will be more likely to adopt a given technology if it is more tech-savvy (higher T_f), or if it recently invested in other advanced technology, i.e. when the technology gap $I_{\tau_{f,t}} - I_{\tau_{f,t-1}}$ is small.

Different technologies will change different aspects of the production technology, potentially affecting either the automation of tasks, the benefits from remote work, the cost of communicating with managers, etc. While this model is kept deliberately general, in this paper I will focus on a particular sequence of technology waves that reflects the large changes experienced during the 2020-2024 period: First, a change in the attractiveness of remote work technology as a result of the Covid pandemic. Second, a change in the potential for automation of particular tasks as a result of the proliferation of Generative AI based tools.

D. Technology Wave #1: Remote work

While there were certainly firms that allowed for remote work before the Covid pandemic in 2020, the sudden need to continue work when forced to work-from-home during lockdowns led to both a large increase in the adoption of remote work in "teleworkable" occupations, as well as large investments, and rapid improvements, in the technology tools enabling work-from-home, e.g.virtual meeting and collaboration software.

Here, remote work is assumed to provide an additional productivity boost r_j to all the tasks done in an occupation, as shown in equation 1. This term can vary across occupations, such that there might be "teleworkable" jobs with a high r_j and other jobs where r_j is small or even negative.

Based on the model above, a firm will adopt remote work (indexed by R) rather than stay non-remote (NR) if $\ln y^{\mathrm{R}}_{fj} - \ln y^{\mathrm{NR}}_{fj} > c^{\mathrm{R}}_f$, which can be written as

$$(j-k_{fj})r_j + (j-k_{fj})\ln\left(\frac{1-D^R_f}{1-D^{NR}_f}\right) + (e^j - e^{k_{fj}})\ln\left(\frac{Q^R_f}{Q^{NR}_f}\right) > c^{\mathrm{R}}_f$$

where R and NR again indicate optimal decisions conditional on going remote or not going remote. Note that we have previously derived that $D^R_f > D^{NR}_f$ and $Q^R_f < Q^{NR}_f$, such that the last two terms on the left are negative—remote work requires more time spent on decisions by the remote worker, and also decreases overall decision quality, which both represent a cost to be weighed against any potential productivity benefits.

Note that this model above generates a number of empirical predictions for the patterns of remote work adoption among firms:

1. More teleworkable occupations and firms (higher remote work benefit r_j) are more likely to adopt remote work.

2. More tech-savvy firms (higher T_f) are more likely to adopt remote work for a given occupation.

3. Firms with a higher level of existing ICT investments (a smaller technology gap $I_{\tau_{f,t}} - I_{\tau_{f,t-1}}$) are more likely to adopt remote work

4. Higher adoption of remote work leads to an increase in demand for decision-making skills and experience—"upskilling"—in the firm's workers

Some of these predictions are already supported by existing findings in the remote work literature, e.g. the teleworkability measure by Dingel and Neiman (2020) has been shown to predict at least part of the variation in actual remote work adoption (Hansen, Lambert, Bloom, Davis, Sadun, and Taska, 2023). In this paper, I will provide novel evidence for predictions #2, #3, and #4.

E. Technology Wave #2: Generative AI and the technology ladder effect

The more important implications of the model above are those that concern what happens to the adoption of a second technology wave as a function of a firm's adoption of the first. While one could apply this framework to automation technologies more generally, I will focus on the effects of generative AI, and how we would expect the adoption of remote work to affect it.

I model the effect of generative AI tool availability as pushing the automation boundary k_j upward. That is, if tasks are sorted by j, then the frontier of automatable tasks expands to

$$k^{\mathrm{G}}_{fj} = k_{fj} + \underbrace{\mathrm{GenAIPotential}_j \times \mathbb{1}[\mathrm{Adoption}]_{\mathrm{f}}}_{\Delta k_{fj} \text{ with Gen. AI}}$$

Here, $\mathrm{GenAIPotential}_j \geq 0$ measures how amenable occupation j is to the new technology, i.e. what share of its tasks are exposed to generative AI automation. Whether this exposure leads to automation at the firm depends on $\mathrm{Adoption}_f \in \{0,1\}$ which indicates whether a firm invests in generative AI adoption. If a firm invests the necessary ICT resources, it moves more tasks into the automatable set. Hence, the fraction of tasks requiring actual worker effort shrinks from $\left[k_{fj}, j\right]$ to $\left[k^{\mathrm{G}}_{fj}, j\right]$.

Note that when k_j grows, more tasks become automated, so fewer tasks remain for labor—but because $\delta'(x) > 0$ the tasks that remain benefit more from higher-level decision-making. The firm thus adopts generative AI if $\ln y^{\mathrm{G}}_{fj} - \ln y^{\mathrm{NG}}_{fj} > c^{\mathrm{G}}_f$, which is equivalent to

$$(k^G - k_{fj}) - (k^G - k_{fj}) r_j \times \mathbb{1}[\mathrm{Remote}_f] - \alpha^G - (k^G - k_{fj}) \ln\left(1 - D_f\right) - (e^{k^G_{fj}} - e^{k_{fj}}) \ln Q_f > c^{\mathrm{G}}_f$$

where $\alpha^G = (j - k^G_{fj}) \ln(j - k^G_{fj}) - (j - k_{fj}) \ln(j - k_{fj}) < 0$. Here, the first term represents the gain from automated production, the second, third and fourth term capture the reduced human output, and the last term is the reduction in the impact of human decision quality as a result of adopting generative AI. Note that this equation provides another prediction which I will test in the data:

5. Firms with higher levels of technical ability or recent investment in technology skills

are more likely to adopt generative AI.

Remote work effect on generative AI adoption. How does the adoption of remote work affect the decision of whether to adopt generative AI technology?

The difference in net benefit from generative AI adoption between remote and non-remote firms is

$$\left[\ln y^{\mathrm{G}}_{fj} - \ln y^{\mathrm{NG}}_{fj} - c^{\mathrm{G}}_{f}\right]\Big|_{R} - \left[\ln y^{\mathrm{G}}_{fj} - \ln y^{\mathrm{NG}}_{fj} - c^{\mathrm{G}}_{f}\right]\Big|_{NR}$$
$$= -(k^{G} - k_{fj})r_j - (k^{G} - k_{fj})\ln\left(\frac{1-D^{R}_{f}}{1-D^{NR}_{f}}\right) - (e^{k^{G}_{fj}} - e^{k_{fj}})\ln\left(\frac{Q^{R}_{f}}{Q^{NR}_{f}}\right) + (c^{\mathrm{G}}_{f}\Big|_{NR} - c^{\mathrm{G}}_{f}\Big|_{R})$$

Note that we the second and third terms—the human output loss due to generative AI adoption—are smaller, i.e. less negative, for a firm that has previously adopted remote work.[3] The last term reflects the fact that the cost of investing in generative AI $c^{\mathrm{G}_f}_{f}$ will be lower (and thus the adoption of generative AI more beneficial) if the firm previously adopted remote work as it can build on the existing ICT infrastructure. However, the $(k^{G} - k_{fj})r_j$ term implies that remote firms are disincentivized from adopting generative AI if they perceive large benefits from work-from-home, which have been assumed to scale with the share of tasks done by humans.

If I make the plausible assumption that the ICT investment cost savings for generative AI adoption when already having implemented remote work are comparatively large relative to the work-from-home productivity boost for the automated tasks, i.e. that

$$c^{\mathrm{G}}_{f}\Big|_{NR} - c^{\mathrm{G}}_{f}\Big|_{R} > (k^{G} - k_{fj})r_j,$$

then we get **the technology ladder effect:** *firms that adopt remote work have a higher incentive to also adopt generative AI*. Even if this condition does not hold, we might still find a technology ladder effect, but it becomes an empirical question which of the channels dominates. Testing whether this effect exists is one of the key analyses in the empirical sections below.

Generative AI effects on remote work. Conversely, does generative AI adoption impact a firm's incentive to continue using remote workers? The change in output from allowing

[3] Here, we can use the envelope theorem to ignore reoptimizations of the decision intensity in the remote and non-remote state when considering generative AI adoption.

remote work can be written as

$$\ln y^{\mathrm{R}}_{fj} - \ln y^{\mathrm{NR}}_{fj} = (j - k_{fj})\left(r_j + \ln\left(\frac{1 - D^R_f}{1 - D^{NR}_f}\right) + \frac{(e^j - e^{k_{fj}})}{(j - k_{fj})}\ln\left(\frac{Q^R_f}{Q^{NR}_f}\right)\right), \tag{3}$$

where it can be shown that

$$\frac{\partial}{\partial k_{fj}}\left(\frac{(e^j - e^{k_{fj}})}{(j - k_{fj})}\right) > 0,$$

or, intuitively, that the average decision-making sensitivity of tasks increases with automation, as lower-complexity tasks are more likely to be automated. Because $\ln\left(\frac{Q^R_f}{Q^{NR}_f}\right) < 0$, this means that equation 3 is decreasing in k_{if}, and the overall benefit from remote work declines with greater automation. This means that the model predicts a **technology substitution effect:** *higher adoption of generative AI should lead to a decline in the use of remote work technology, if it was previously adopted.*[4]

IV. Empirical Approach

To test whether there is in fact a "technology ladder effect", we want to estimate the effect β of having a greater share of remote jobs on firms' investment in generative AI skills. This effect is estimated from regressions of the form

$$GenAIJobShare_i = \alpha + \beta RemoteJobShare_i + Controls_i + \varepsilon_i, \tag{4}$$

where the unit of observation i can be a firm or an occupation-by-firm unit. The $Controls_i$ are detailed below when discussing how I address identification concerns. While the main estimation will be cross-sectional, using job posting data for the 12 months ending in, and including, September 2024, to construct the dependent variable, some of the control variables are constructed in earlier periods to capture past characteristics of the firm, occupation, or location.

A. Identification issues

One key concern that arises from the conceptual framework for generative AI technology adoption discussed above, is that some firms may be generally more inclined to both adopt remote work and generative AI, not because the former causes adoption of the latter, but

[4] Note that I am assuming that for the purpose of the decision of whether to continue letting workers work remotely, the technical infrastructure is not relevant, as there is no way to "recoup" the original outlay for ICT capital to enable work-from-home when later eliminating remote work.

rather because the types of tasks suitable for remote work might overlap with those suitable for generative AI tools.

To see that this is a relevant concern, I compare a proxy for the remote work suitability of an occupation—the "teleworkability" measure by Dingel and Neiman (2020)—to the measure of generative AI exposure at the occupation level from Eisfeldt, Schubert, Zhang, and Taska (2023). Figure 4, Panel A, shows that there is a positive relationship between occupations having tasks that are suitable for remote work and tasks that are exposed to generative AI capabilities.

Another concern arises from industry- or firm-level differences in the ability and willingness to adopt new technologies in general, which may drive adoption speeds for both remote work and generative AI, and which would lead to omitted variable bias if we do not account for it in the estimation.

The ideal setting for estimating the effect of remote work adoption on generative AI adoption would therefore require a setting where we can compare groups of jobs that have similar *suitability* for both remote work and generative AI deployment, and also are at companies with similar "tech savvy" or innovative capacity. The ideal experiment to identify causal effects would then require one group of these jobs to experience greater prevalence of remote work for an exogenous reason, so that we can compare generative AI adoption rates to see what the magnitude of the causal channel operating *through* remote work adoption is.

I approximate this natural experiment by controlling for potential confounders and instrumenting for remote job prevalence using exogenous variation that is plausibly unrelated to firm-level differences in unobserved characteristics that might be driving generative AI adoption. As control variables, I include Dingel and Neiman (2020) teleworkability and Eisfeldt et al. (2023) generative AI exposure scores to capture the intrinsic nature of the tasks performed in different firms and occupations that might make them more or less suitable for adopting these technologies. Moreover, the most stringent specifications include fixed effects at the level of the firm or occupation that capture general differences in tech-savvy, or in the tendency to adopt either of the technologies of interest, as well as controls for the education level of hiring that might capture the ability of employees to implement innovations.

B. Instruments

To identify exogenous variation in the remote job share at the firm level, I exploit a novel source of variation in whether a firm adopts remote work at a high rate in a particular location: the interaction between labor market *competition* and the *ability* to let employees work remotely. That is, many studies (e.g. Maestas et al. (2023), Powell and Wenger (2024)) have found that workers consider the ability to work remotely as a sizable non-monetary benefit. As a result, similar to the way that workers' outside options encourage firms to match wages on offer elsewhere (Schubert, Stansbury, and Taska, 2024), labor market competition induces firms to offer remote work options in labor markets where *other* employers are offering this perk.

While the actual adoption of remote work by other employers in particular labor markets is both difficult to observe (as remote job locations are, by definition, not well defined in job postings), and might be simultaneously determined with post-pandemic choices by the firm of interest, the *average pre-pandemic ability* to work remotely in the labor markets that a firm hires in is both observable and unlikely to be driven by the focal firm's ex post adoption behavior. Thus, I construct a firm-level instrument for remote work adoption as

$$\begin{aligned} Z_f &= \left(\sum_m \phi_{fm,2019} T_{m,2019}\right) \times T_{f,2019} \\ &= \underbrace{\text{Avg. Labor Market Teleworkability}_{f,2019}}_{\substack{\text{Remote work adoption potential} \\ \text{of the firm's labor market pre-Covid}}} \times \underbrace{\text{Firm Teleworkability}_{f,2019}}_{\substack{\text{Firm remote work adoption} \\ \text{potential pre-Covid}}}, \end{aligned}$$

where $T_{m,2019}$ is the average Dingel and Neiman (2020) teleworkability among job postings in a particular MSA based on 2019 job postings, and the MSAs are weighted by the share $\phi_{fm,2019}$ of all firm f hiring done in each location m as of 2019. $T_{f,2019}$ is the average teleworkability among job postings by firm f in 2019.

As I also want to be able to estimate exogenous variation across occupations *within firms*, I construct occupation-by-firm-level instruments based on a similar intuition. For occupations where the remote work share was higher at the national level post-Covid (but before the ChatGPT release) in 2021-2022, employers who are able to let their workers work remotely likely face more labor market pressure to grant this perceived perk. Thus, adoption of remote work in an occupation-by-firm cell can vary in response to this labor market channel, without it having a direct effect on within-firm incentives to adopt generative AI in particular occupations. To be specific, the occupation-by-firm instrument is constructed by interacting both the average labor market teleworkability in a firm's hiring markets as of 2019 with the remote work share in the occupation during the late pandemic years 2021-2022:

$$Z_{fo} = \left(\sum_m \phi_{fm,2019} T_{m,2019}\right) \times \text{RemoteWorkShare}_{o,\text{'}21-22}$$

Exclusion restriction. These shift-share instruments rely only on pre-Covid job com-positions in different locations, firms and occupations, and exogenous national trends in remote work before generative AI technology was salient and are therefore unlikely to be correlated with endogenous generative AI adoption choices by a firm, other than through the remote work channel. As a firm's teleworkability or exposure to particular labor markets on their own might be correlated with particular unobservable firm characteristics, the IV estimation will control for the uninteracted components of the instrument. The identification relies on the fact that the *interaction* between a firm's teleworkability and its labor market teleworkability is not the result of a deliberate pre-pandemic selection that could drive a firm's tendency to adopt technologies over time.

Unit of observation. Depending on the particular dimension of the variation in generative AI adoption that we are interested in, a different unit of observation is appropriate. One question is whether the *same firms* are seeing higher remote work adoption and generative AI adoption, which matters for inequality in productivity across the economy as some firms might see compounding effects of technology, and might also provide evidence about the degree to which there is variation in corporate strategy across firms. This question is best studied using firm-level evidence. At the same time, there are questions of whether generative AI adoption is more prevalent in the same occupations where remote work was adopted, which speaks to the degree to which these technologies complement or substitute for one another *within* particular jobs. I will use a firm-by-occupation sample to study the latter questions, such that I can identify differences in effects across occupations within the same firm.

V. Remote Work Impact on Skills and Generative AI

In this section, I first explore what firm characteristics are associated with greater adoption of remote work. Then, I estimate the causal effect of remote work adoption on changes in the skill composition of a firm's hiring, and provide evidence of the "technology ladder effect:" remote work adoption has a positive causal effect on the subsequent investment in generative AI skills.

A. Determinants of remote work adoption

What type of firm is more likely to adopt remote work? The conceptual framework suggests that firms with greater levels technological capabilities, and greater recent investment in technology skills should be more likely to invest in remote work technology. I test this prediction and the effect of other firm characteristics in regressions of the form

$$\text{RemoteWorkShare('21-'22)}_i = \alpha_{ind} + \beta \ \text{FirmCharacteristic(2019)}_i + \text{Controls}_i + \varepsilon_i,$$

where all independent variables are standardized and the controls include the 2019 value of the dependent variable, so the coefficients can be interpreted as the effect of a standardized difference in the characteristic on changes in the remote work share. To proxy for the effect of simply hiring for roles that are more suitable for remote work, the control variables also include firm-level teleworkability in 2019 and 2021/2022, as well as the company's share of jobs requiring a college education in 2019.

The results are shown in Figure 5: the first two lines of the graph show the effect of the share of employment in LinkedIn data for the firm that consists of computer occupations or of occupations that usually have a high share of data management skills as defined in Eisfeldt et al. (2023). These measures capture the pre-pandemic level of technology skills in a firm and show a strong positive association with remote work adoption.

Similarly, the coefficients in rows 3-5 capture various dimensions of technology skill prevalence in pre-pandemic hiring of the firm and show that hiring for data management skills and machine learning skills in particular predicts greater remote work adoption. Thus, these findings are consistent with the technological capability mechanism in the model.

While the model does not make explicit predictions for other organizational and financial characteristics, these can provide context for understanding why some firms adopt remote work: the figure shows that firms that are larger or less R& D-intensive, or that have a higher labor share or labor intensity in production[5] are more likey to adopt remote work. With regard to financials, measures of higher earnings, such as gross profitability, ROA, and ROE, all predict higher remote work.

B. Remote Work Impact on Skills

This section tests how the adoption of remote work changed hiring patterns with regard to skills. These results will be important for understanding through which mechanism the technology ladder effects on subsequent generative AI adoption might be operating. I estimate specifications of the form

$$\text{Skill(2022)}_i = \alpha + \beta \ \text{RemoteWorkShare('21-'22)}_i + \gamma \text{Skill(2019)}_i + \text{Controls}_i + \varepsilon_i, \qquad (5)$$

[5]The latter is defined as ln(Employment/PP&E).

where the dependent variable captures different measures of the composition of the firm's hiring with regard to indicators of skill in its job postings. These regressions also control for the past level of the dependent variable pre-pandemic, so the estimated coefficients capture the effect on changes in the skill composition of job postings between the period before and after the lockdown period of the pandemic.

Figure 6 shows the results of the IV estimation at the firm level (and Appendix Figure 14 shows the OLS estimates), which additionally control for a rich set of pre-pandemic hiring characteristics to capture potential confounders in hiring skill trends.

First-stage. In order to identify exogenous variation in remote work adoption, I use the IV strategy discussed in Section IV. To visualize the relationship that underlies this variation, Figure 7 plots the relationship between the interaction of labor market teleworkability and firm teleworkability, and how it predicts firm level remote work shares (controlling for the uninteracted teleworkability terms). As the figure shows, the instrument has a strongly positive relationship with the endogenous remote work prevalence at the firm (see also Table II, column (5) for the first-stage coefficient including a full set of control variables). This strong relationship is reflected in the first-stage Kleibergen-Paap F-statistics. While these are not explicitly shown in the graph, each regression in Figure 6 includes a sample size of ~ 153K firms, and the first stage is strong, with Kleibergen-Paap F-statistics of >33 throughout.

Upskilling. First, I explore whether firms change the formal requirements for workers' experience or education when increasing the remote share of their workers, i.e. whether there is upskilling as a result of the technology adoption. The results shown in rows 1-3 of Figure 6 show that firms that adopt remote work at a higher rate increase their hiring of workers with at least a college degree and with at least 5 years of experience. This shows that firms are *upskilling* their hiring in response to a greater remote work share.

Job skills. Which particular skills are firms more likely to hire for when they adopt remote work? In the following rows of the graph, I consider how the mentions of particular skills in job postings, or the mix of occupations that tend to have particular skills, evolve with an exogenous change in remote work. I focus on key skills that might matter for how remote work fits into the firm's work processes, such as communication, decision-making or technology skills.

The results show that the firm does not shift its hiring towards roles that tend to involve more interactiveness, "inflexible" client responsibilities as defined by (Goldin, 2014), or towards mentioning more teamwork or communication skills in job postings. I only find evidence that roles requiring greater social skills as defined by Deming (2017) are more likely to appear in a firm's hiring when remote work is adopted.

In contrast, I find evidence of a shift in hiring towards decision-making roles: firms increase the share of job postings that hire for manager positions, for roles that have high decision-making intensity Deming (2021) and also hire more for roles that involve leadership skills (Schubert et al., 2019).

There is even stronger evidence of a shift in hiring towards roles that tend to involve data management skills and towards computer occupations. Moreover, the share of job postings mentioning data management, data science, machine learning, or deep learning skills increases significantly when remote work increases.

These results confirm the predictions from the model that greater adoption of remote work should lead firms to increase the decision-making intensity of their jobs, and also that remote work adoption requires higher investments in technological capabilities. The next section estimates the consequences of the greater prevalence of remote work for generative AI adoption.

C. Remote Work Impact on Generative AI Adoption

To test the key hypothesis that there exists a "technology ladder effect," this section estimates the causal effect of remote work on Generative AI adoption both across firms, and across occupations within firms. Then, I explore heterogeneity with regard to which occupations are the ones that adopt Generative AI technologies in response to higher remote work prevalence at a firm, in order to better understand the mechanism for the effect.

Firm-level results. To what degree is the correlation between remote work shares at firms and their tendency to invest in hiring workers with generative AI skills causal? I use the IV approach to estimate equation 4. and the results are shown in Table II. Column (1) shows the OLS results, and columns (2)-(4) control for increasingly stringent measures of the underlying firm characteristics that might be jointly driving both remote work adoption and generative AI investments. The coefficient corresponds to a % elasticity between the remote share and the generative AI skill share in the firm's job postings, such that the most stringent specification in column (4) suggests that a 10 pp higher remote share causes about a 0.8 pp higher generative AI skill share. The control variables include proxies for the task-level teleworkability (Dingel and Neiman, 2020) and generative AI exposure (Eisfeldt et al., 2023) at the firm, as well as industry sector fixed effects and the level of education required for average job postings at the firm. These controls mean that the effect is unlikely to be driven by a sorting of jobs that are more suitable for both technologies into the labor markets that are affected by the exogenous remote work variation induced by labor market competition. Note that the IV estimates are substantially larger than the OLS estimates, suggesting that firms that endogenously choose to offer remote work tend to be less likely to adopt generative AI.

Within-firm variation. Is the coincidence between remote work and generative AI driven only by firm-level dynamics, or is there also a causal effect of one on the other *wthin* firms, across occupations? I estimate these within-firm causal effects using the IV approach that exploits occupation-level differences in the tendency to adopt remote work during the pandemic, interacted with the firm's labor market pressure to adopt remote work.

Table III shows the results for this within-firm effect: columns (1)-(3) correspond to adding occupation fixed effects and similar control variables as were already included in Table II, and column (4) adds firm fixed effects. This means that the latter effect is only identified off within-firm variation across occupations. The estimated effect suggests that higher remote work prevalence still has a large positive causal effect across occupations within a firm (and across firms within an occupation), with a size almost twice that of the across-firm effect.

These results mean that, while differences in corporate processes and capabilities as a result of firm-level changes in response to remote work can perhaps explain part of the puzzle of why the adoption of these two technologies is correlated, this is not the full story. The inclusion of occupation and firm fixed effects means that the effects cannot be explained purely by a change in the composition of hiring by firms towards occupations that tend to use generative AI. The large within-firm causal effects suggest that *particular jobs* become more suitable for generative AI if those jobs themselves adopted higher rates of remote work at that firm. In order to understand why remote work might have this effect, we next explore how job and firm characteristics increase or decrease the magnitude of these effects.

D. Heterogeneity of remote work effects on generative AI

In this section, I estimate whether particular firm characteristics are associated with higher or lower impacts of remote work adoption on generative AI adoption. I estimate interacted regression models of the form

$$\begin{aligned}100 \times \text{GenAIJobShare(‘23-‘34)}_i = &\beta \text{ RemoteWorkShare(‘21-‘22)}_i + \alpha_{ind} + \text{Controls}_i \\ &+ \gamma \mathbb{1}[\text{High}_i] \times \text{ RemoteWorkShare(‘21-‘22)}_i + \varepsilon_i\end{aligned}$$

where the “High” indicator is computed for different firm characteristics and indicates that the firm is above the average across firms for the measure.

The results of estimating these interacted models are shown in Figure 8, where I show both the estimated baseline effect of remote work on generative AI adoption for the “low” group (lower panel), and the estimated interaction coefficient that captures the difference in remote work effects between the high and the low group for each characteristic (upper panel).

I find a number of interesting patterns that align with the proposed model of technology adoption: On the one hand, the "low" group coefficients confirm that the significant positive effect of remote work adoption on generative AI adoption is not driven by any particular sub-group of firms, as the baseline effects remain significant in all of the interactions.

On the other hand, there is systematic variation in the size of the effect with particular firm characteristics: (a) firms with greater advanced degree hiring are more likely to adopt generative AI when workers are remote; (b) firms that normally hire for occupations that are more social skill-, communication- or interaction-intensive, or which explicitly mention communication skills are less responsive in their generative AI adoption to the remote work share; (c) firms that hire for jobs that are more decision-making intensive are less likely to increase generative AI adoption when their remote work shares are high; and (d) firms with more hiring in tech *roles* (computer occupations or data management intensive occupations) are not more responsive in their generative AI adoption, but firms that more frequently mention specialized tech *skills* in any role are significantly more responsive. The latter finding may indicate that firms that increase their level of digitization across all roles are more likely to then be able to adopt generative AI technology.

We can try to enrich this pattern further by estimating whether particular *occupation* characteristics are associated with higher or lower impacts of remote work adoption on generative AI adoption when holding overall firm effects constant. Again, I define "High" indicators at the national level using O*Net data for all measures that indicate that occupations are above the job posting-weighted average for the measure (except for job zones and decision-making, where the indicator is applied for absolute values of at least 4 and 8, respectively).

The results, shown in Table IV show that the impact is larger within firms in jobs that require more preparation (column 1), or more decision-making (column 2), but smaller in jobs that require more social skills (column 3), are more interactive (column 5), more leadership-intensive (column 6), and less flexible (column 7).

These results suggest that firms are shifting their hiring more towards generative AI skills in response to earlier remote work adoption for jobs that are analytically demanding (which tend to be highly exposed to generative AI productivity improvements according to Eisfeldt et al. (2023)). In contrast, roles that have less complex relationships with other people inside or outside the organization are less likely to see generative AI technology adoption after adopting remote work. As I showed earlier, this aligns closely with the roles that proliferate within firms in response to remote work adoption. That is, these results provide evidence that the particular changes in a firm's hiring composition towards more decision-making intensive and higher-skilled positions makes it more likely that remote work results in higher generative AI adoption. Moreover, this finding also aligns with intuition captured by one of the quotes at the beginning of this paper: workers that have regular interactions with co-workers are less likely to be replaceable by AI-driven automation.

The next section explores whether the rise in generative AI adoption—partly driven by remote work itself—has an effect on the prevalence of remote work.

VI. Generative AI Effects on Remote Work

In this section, I provide firm-level evidence on how the change in hiring patterns at firms in response to Generative AI technology complements or substitutes for firms' use of remote workers.

The first question I explore is whether the stylized fact pattern shown in Panel B of Figure 2, and described in Section II, of higher later generative AI adoption being associated with a strong reversal in remote work shares at exactly the moment when ChatGPT was released is likely to represent a causal "technology substitution effect" or might be coincidental. As the reversal in the figure at the time of the ChatGPT release is quite stark, any alternative explanation would require a shock that could lead to a reversal in remote work shares that precisely coincides in timing with the ChatGPT release *and* is more likely to affect firms with high generative AI adoption. As the graph shows, there is some concern that arises from the fact that high generative AI adoption is clearly not randomly assigned with regard to remote work shares—in fact, I have argued in the previous section that higher remote work adoption eventually *causes* greater generative AI adoption. As a result, firms that had higher later generative AI adoptions also had steeper run-ups in remote work earlier in the pandemic. Any causal effect in the other direction—from generative AI adoption to remote work—therefore needs to try and hold remote work adoption constant when comparing firms around the time of the ChatGPT release event.

Firm-level trends. To show the variation in the raw data that underlies this estimation and to verify that the timing of generative AI innovations is associated with remote work prevalence even at the firm level, I do a similar analysis to that in Panel B of Figure 2, but for firms. In Figure 9, I sort firms by their quartile of generative AI exposure. The reason to use generative AI exposure rather than later generative AI adoption here is that we already know that actual generative AI adoption will be affected by remote work trends, so this might lead to reverse causality in the estimation. In contrast, the firm's task-based exposure to generative AI, measured before the ChatGPT release, is unlikely to be shaped by the differential remote work trends after the release that we're interested in. Comparing the firm-level remote work trends by generative AI exposure shows similar patterns to the occupation-level results: firms with higher exposure have steeper run-ups in remote shares that reverse in exactly the quarter when ChatGPT is released.

Synthetic difference-in-differences. I want to test more formally whether these differential trend breaks in remote work shares around the ChatGPT release period might be driven by generative AI innovations. While many event studies use a difference-in-differences design that compares treated and control groups under the assumption of parallel trends between these groups, we already know that this assumption is unlikely to hold unconditionally based on the results in the previous section: high remote work share firms are more likely to have high generative AI exposure and remote work share also causally affects generative AI adoption. In traditional difference-in-differences designs, one would use control variables to try and capture the common variation in the confounding variable, which would mean trying to incorporate all the control variables that can capture potential drivers of differential remote work share trends at the firm level. However, as there is not necessarily a definitive list of these drivers, one would worry that the control and treatment group are not fully comparable in terms of their remote work trends even after including suitable observables.

A more appropriate methodology in this case is therefore the synthetic difference-in-differences (SDID) design proposed by (Arkhangelsky et al., 2021): instead of ex ante selecting which control variables might align remote work trends in the pre-event period between firms, this methodology first estimates which untreated firms have remote work trends that are most similar to the pre-trend of the treated units, and uses a weighted average of the most-comparable firms to create a "synthetic" control group. The estimation of post-event relative trends between the treated and control groups then proceeds analogous to a difference-in-differences estimation, but weighting potential control group firms based on the optimal weights, and also applying time weights that optimally put higher weights on pre-periods that are more comparable to post-event periods for the control group.

Conceptually, this corresponds to determining the treatment effect τ of being in a high generative AI exposure group in a regression equation of the form

$$\text{RemoteWorkShare}_{it} = \mu + \alpha_i + \gamma_t + \tau \mathbb{1}[\text{Post-ChatGPT}]_t \times \mathbb{1}[\text{High Gen. AI Exposure}]_i + \beta' X_{it} + \varepsilon_{it}, \tag{6}$$

which include firm fixed effects α_i and time fixed effects γ_t, which absorb level differences between firms, and national trends in the remote work share. The regression can also account for control variables X_{it} that can account for additional variation that is not captured by the time and firm fixed effects. More specifically, the treatment effect τ is estimated with SDID as

$$\left(\widehat{\tau},\widehat{\mu},\widehat{\alpha},\widehat{\gamma}\right)=\underset{\tau,\mu,\alpha,\gamma}{\arg\min}\left\{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\text{RemoteWorkShare}_{it}-\mu-\alpha_i-\gamma_t-\text{Treated}_{it}\tau\right)^2\widehat{\omega}_i^{\text{sdid}}\,\widehat{\lambda}_t^{\text{sdid}}\right\} \tag{7}$$

where Treated stands for the interaction $\mathbb{1}[\text{Post-ChatGPT}]_t \times \mathbb{1}[\text{High Gen. AI Exposure}]_i$ between the post-release period indicator and the high generative AI exposure group assignment. The difference to conventional difference-in-differences comes from the optimal weights $\widehat{\omega}_i^{\text{sdid}}$ and $\widehat{\lambda}_t^{\text{sdid}}$ that are estimated in a first step to create a control group that matches the treatment group's trend in the remote work share (as opposed to differences in levels which are absorbed into the firm-level fixed effects).[6]

Event study data. In order to use the SDID estimator, I need a balanced panel of company-by-period observations. I retain all firms that have at least 10 job postings in all quarters from Q1 2021 to Q3 2024, which is the sample period for the event study estimation, consisting of 7 quarters before and after the ChatGPT release in Q4 2022. To define the treated group with high generative AI exposure, I sort firms by the continuous exposure variable and assign the top decile of firms by exposure to the treated group. Note that this means that the estimated effect does not compare firms with high exposure to firms with zero exposure, but rather to a synthetic control group that has *some* exposure and similar remote work trends to the highest exposure groups.

Generative AI exposure and generative AI adoption. While the use of generative AI exposure based on the task composition of jobs, instead of actual generative AI adoption avoids the endogeneity issues associated with realized firm choices to adopt the new technology, it raises the question of whether the Eisfeldt et al. (2023) measure of firm-level exposure to generative AI actually predicts firm-level adoption of generative AI. One way to validate this "first-stage" relationship is in the cross-section: Figure 10 shows how the share of all job postings (panel A) and remote job postings (panel B) at the firm level in YTD Sep. 2024 varies with the firm's generative AI exposure. As the figures show, there is a monotonically increasing relation between the predicted exposure measure and the actual adoption across firms. I can also estimate this relationship in the same SDID event study setting as the remote work effects that we're interested in. Column 1 of Table V shows the estimated post-ChatGPT effect of being in the top exposure decile on the generative AI share of job postings. The estimate shows that the generative AI share increases by 0.2pp

[6] I implement this estimation procedure using the `sdid` package in Stata, which is described in Clarke, Pailanir, Athey, and Imbens (2023).

on average more in the top decile than in the matched control group with lower exposure. For comparison, the generative AI exposure score is 0.54 in the treated group and 0.35 in the synthetic control group, and generative AI adoption is 0.7pp in the treated group and 0.1pp of job postings in the control group as of Q3 2024.

Generative AI adoption heterogeneity by firm hiring characteristics. To close the loop on whether the characteristics that are engendered by greater remote work adoption then make it more likely that a firm in fact adopts generative AI, I split my sample based on the characteristics of a firm's hiring in 2022 to see if particular hiring patterns lead to a stronger adoption of generative AI. The results are shown in Figure 11: I find that firms with more decision-making intensive hiring and that hire for more technical skills are more likely adopt generative AI after the release of ChatGPT. These are exactly the types of hiring that increase with remote work adoption, providing a mechanism for the technology ladder.

Generative AI effects on remote work. How much does the remote job share change for high generative AI exposure firms after the ChatGPT release? Columns 2 qnd 3 of Table V show that the estimated effect on remote work shares is a reduction by 3.4 pp if changes in the teleworkability composition of remote jobs over time are not included as a control variable, and a reduction by 3.5 pp if they are. This is a substantial effect: the treated group has a level of remote work of 18.2% in the pre-period (7.3% for the control group), so the post-release impact of being in the high exposure group corresponds to a 19% reduction on average in remote work prevalence in job postings.

Remote work effect heterogeneity by firm hiring characteristics. Which firm characteristics make it more likely that a firm responds to generative AI adoption with a reduction in remote hiring? I again split the sample based on the characteristics of a firm's hiring in 2022 and repeat the synthetic diff-in-diff estimation for each subgroup. The results are shown in Figure 13: Comparing the above-average firms in the upper panel to the below-average firms in the lower panel, some clear patterns emerge: high generative AI-exposure firms hiring for *fewer* communication-intensive roles (which includes managers) and that hire for *more* technical skills are more likely to reduce their remote work share after the release of ChatGPT. This is consistent with the evidence in Figure 11, where we found that remote work is less likely to lead to generative AI adoption if a firm is communication-intensive. However, the latter figure also found that technology skills enabled generative AI adoption in response to remote work, in the same way that technology skills seem to enable the firm to substitute generative AI for remote workers with the subsequent wave of innovation.

Generative AI effects on the characteristics of remote work. What happens to the composition of remote work in response to high exposure to generative AI? Repeating the same estimation as in equation 7, but with the share of *remote jobs* or *non-remote jobs* that have particular characteristics as the dependent variable, captures whether the decline is concentrated in particular types of remote work and whether the adoption of generative AI further changes the skill mix of a firm's hiring. The non-remote job skill composition results are shown in panel A of Table VI and those for the remote work skill composition in panel B.

Column 1 that the change in the share of generative AI skills in remote work jobs is very similar to that in the non-remote jobs, suggesting that the decline is not due to a higher tendency of adopting generative AI *within* remote work jobs. Columns 2-4 of the same table show that this coincides with an upskilling of the experience distribution, shifting demand away from workers with mid-level experience (who represent the largest group of job postings), leaving entry-level demand unchanged, and significantly increasing hiring of more experienced workers. At the same time, there was no substantial change in the demand for college or advanced degrees among remote workers (columns 5 and 6).

Interestingly, there is strong evidence in Table VI that generative AI adoption increases demand for decision-making skills (column 8) among all workers, and also evidence for a (smaller) increase in communication skills, (column 9), while demand for data management skills among remote workers is unaffected, but increased among non-remote workers (column 7). This provides evidence in favor of the assumption in the model that generative AI adoption is associated with a shift towards more decision-intensive tasks for human workers.

VII. Discussion

The results above tell the following story of how the technology ladder between remote work adoption and generative AI adoption operates: First, many firms adopted remote work in response to greater availability of related tools and a physical need to adopt them during the Covid pandemic, which then changed optimal work processes and firms' skill mix. I find that the change in work processes that resulted from this first technology shock was associated with an upskilling in firm hiring: firms that adopted remote work to a higher degree increased their hiring of more experienced workers (5+ years of experience), which is consistent with the finding that the productivity effects of remote work are more negative for less experienced workers (Emanuel and Harrington, 2024).

At the same time, a higher adoption of remote work caused firms to invest in additional data management skills, and increased the demand for decision-making skills, including hiring additional managers. This is consistent with the increased demands on managers as a result of a reduced ability to train and supervise remote workers. Remote work also required firms to increase their hiring for technical roles, including data management positions, to support the new virtual and digitalized operations. Additionally, I find some evidence that firms increased their hiring for social skill-intensive roles and for teamwork skills. These findings are in line with other studies that have found that firms increased the share of investments going to IT equipment and computers during the pandemic (Barrero, Bloom, and Davis, 2021). Other research has also found that remote work increases the time and effort devoted to communication (Gibbs et al., 2023) and led to a decrease in the amount of information sharing across collaboration networks (Yang, Holtz, Jaffe, Suri, Sinha, Weston, Joyce, Shah, Sherman, Hecht, et al., 2022), which firms might seek to counter-act by investing in hiring for management and team coordination roles that can overcome these issues.

After ChatGPT was released, remote work then facilitated the adoption of generative AI. Firms that were forced to adopt remote work arrangements found it easier or more profitable to respond to the ongoing technology shock due to the surge in the utility and availability of generative AI tools in November 2022. While the causal effect on generative AI adoption is robust across different sub-samples, the heterogeneity tests reveal that technology skills in particular differentiate which firms implemented generative AI at a faster pace in response to initially going remote. This suggests a direct mechanism through with the organizational shifts in response to remote work adoption increase the benefits from the next technology wave: technology skills generally enable the adoption of both technologies and adopting them increases the technological skill level at the firm. As a result, the technologies complement one another, as generative AI adoption can build on the infrastructure already established for remote work.

This effect is stronger within firms in occupations that require more decision-making skills and experience, and fewer social skills, interaction, and direct leadership of others. This provides an explanation for how remote work enables generative AI adoption: as remote work leads firms to change the composition of the roles that they are hiring for towards higher decision-making intensity and more experienced workers, as well as away from social skill-oriented roles, this increases the ability to adopt generative AI tools. While I find that jobs that are suitable for remote work are already more likely to be suitable for the application of generative AI tools to begin with.

However, while remote work enables the use of generative AI tools, the use of the latter also displaces hiring for the former. That is, the event study design around the release of ChatGPT shows that firms that adopt generative AI to a larger degree then reduce their hiring for remote workers. Moreover, generative AI adoption further propels the upskilling of firms' hiring and shifts the composition of remote workers towards even more decision-making skills as generative AI tools complement human ability to structure and evaluate analytical work output. Similarly, firms invest more in technology skills when they adopt generative AI tools. The latter investment seems to then enable further automation of remote work.

An important role is played by the degree to which a company's operations require a lot of communication: remote work leads to some additional hiring for social skill-intensive roles and managers. However, having many roles that require a lot of communication and interaction mitigates the effect of remote work on generative AI adoption and also reduces the degree to which generative AI use—when it happens–substitutes for remote work. This is in line with the quote at the beginning of the paper that interacting with colleagues and customers makes employees harder to automate.

The dynamic of this "organizational technology ladder" raises important issues for policymakers and business responding to technological changes. It suggests that differences in the ability to innovate and transform an organization in response to an initial technology shock can compound into broader competitive advantages over time if the ability to benefit from later technological waves depends on how eagerly an organization embraced the former. This path dependency means that an initial heterogeneity in technology exposure can cascade into some firms and worker groups being systematically affected by later changes in a way that would be difficult to anticipate based on studying these technology shocks in isolation. As I argue in this study, remote work and generative AI technologies are intimately connected in their effect on firms and local labor markets, both by coinciding in the same jobs and by mutually affecting firms' ability and willingness to invest in the other technology.

As both technologies continue to evolve and firms continue to adapt, understanding these technological complementarities is crucial for predicting how labor markets and firm productivity will evolve, and for policymakers and researchers to be able to design and analyze policies that harness these changes for the benefit of society. In addition, the effects on skill demand and heterogeneity of effects for different roles highlight that particular worker groups—particularly those in interactive or technical roles—might be less negatively impacted, even if their position is remote.

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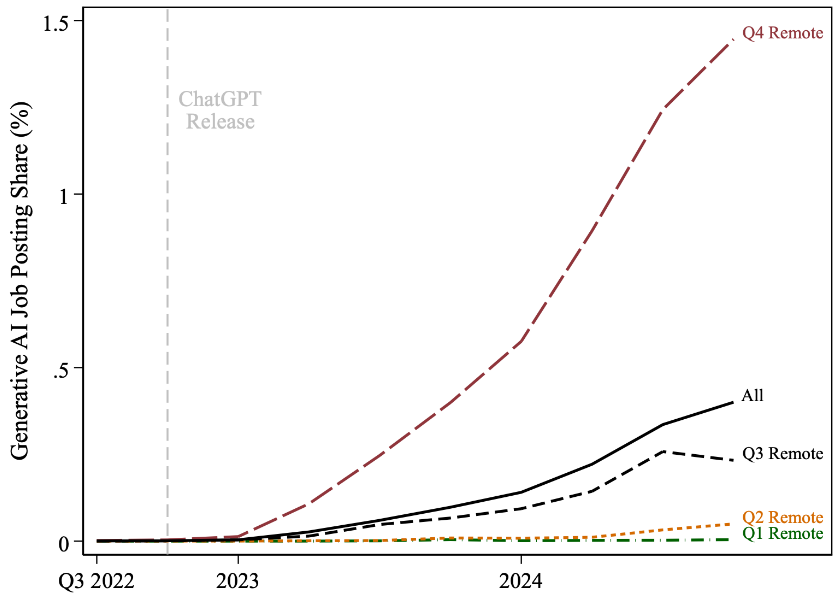
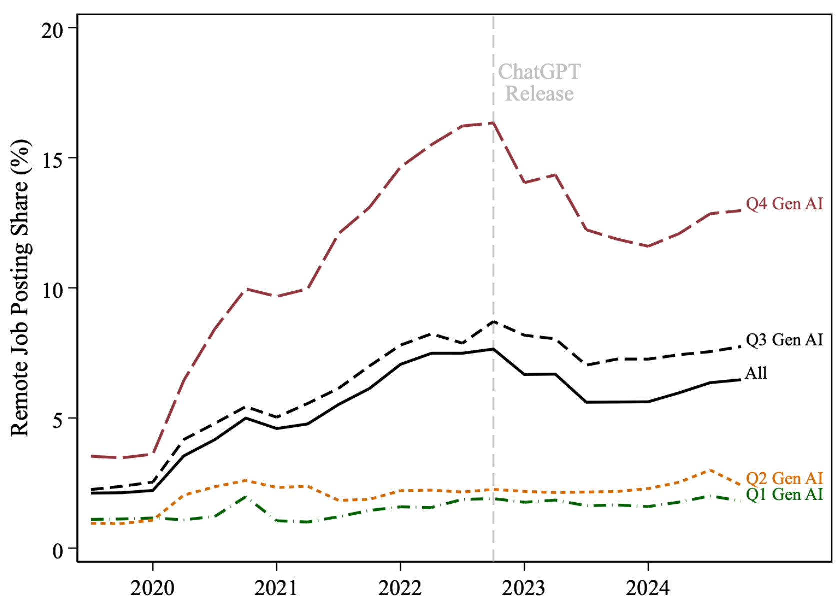
Figures and Tables

Figure 2:
Remote work and occupational generative AI adoption trends.

This figure shows the share of job postings in each quarter that are for jobs that mention generative AI (panel A) or for remote jobs (panel B). In each panel, the occupations are aggregated into job posting-weighted quartiles of adoption of the other technology: panel A shows generative AI adoption by the occupation's quartile of national remote work adoption in 2021-2022 (excl. Q4 2022), and panel B shows remote work share by generative AI demand as of YTD Sep. 2024. The grey drop line indicates the period (Q4 2022) when ChatGPT was released.



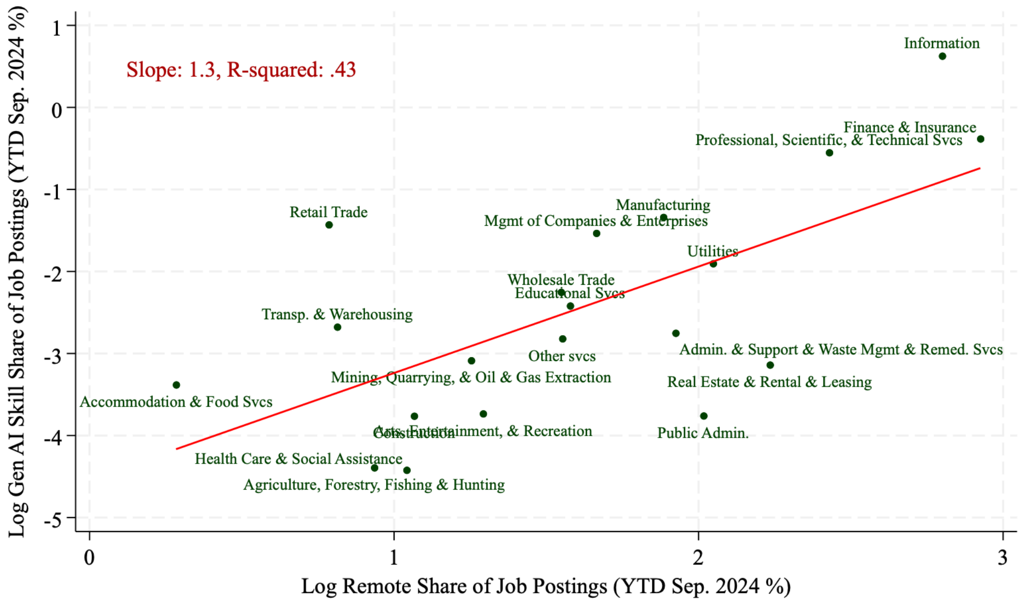
(A) Gen. AI share by remote work quartile



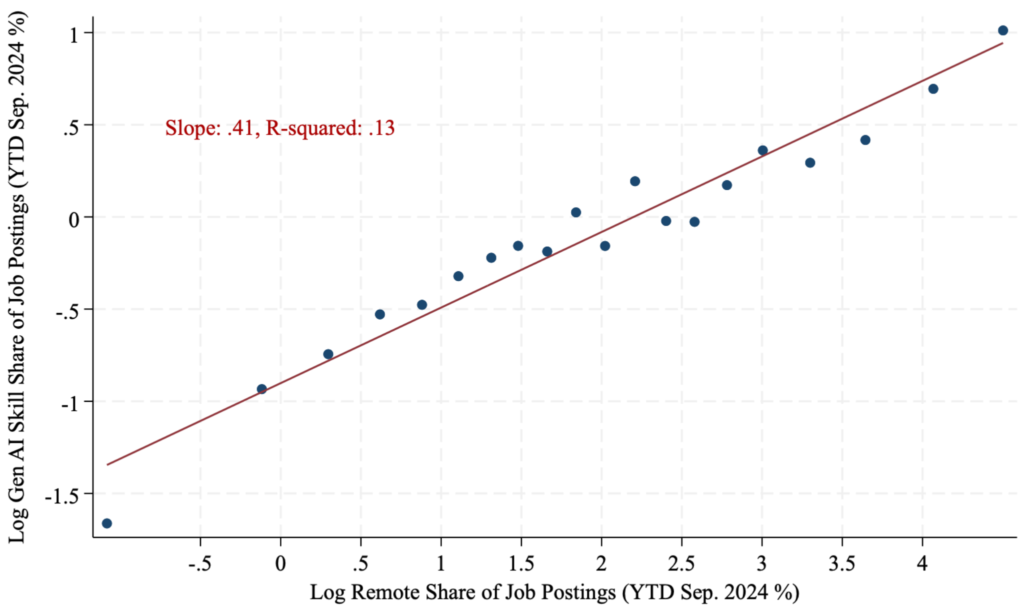
(B) Remote work share by Gen. AI quartile

Figure 3:
Remote work and generative AI at the firm and industry level

These figures plot the share of job postings in the YTD Sep. 2024 period that are for jobs that mention generative AI relative to those that are for remote jobs. In each panel, the job postings are aggregated: into 2-digit NAICS industry sectors in panel A and by company in panel B. Red lines indicate a linear best fit that is weighted by job postings in each cell. Panel B only includes companies that have at least 10 job postings in the sample.



(A) Generative AI and remote work by industry sector



(B) Generative AI and remote work by firm

Figure 4:
Remote Work Suitability and Generative AI Exposure by Occupation

This figure shows the relation between Generative AI exposure and remote work suitability. Generative AI exposure and teleworkability are measured at the SOC 2010 6-digit occupation level based on data from Eisfeldt et al. (2023) and Dingel and Neiman (2020), and aggregated across detailed occupations based on employment weights as of 2022 from the Occupational Employment Statistics. The line of best fit in red is estimated with employment weights.

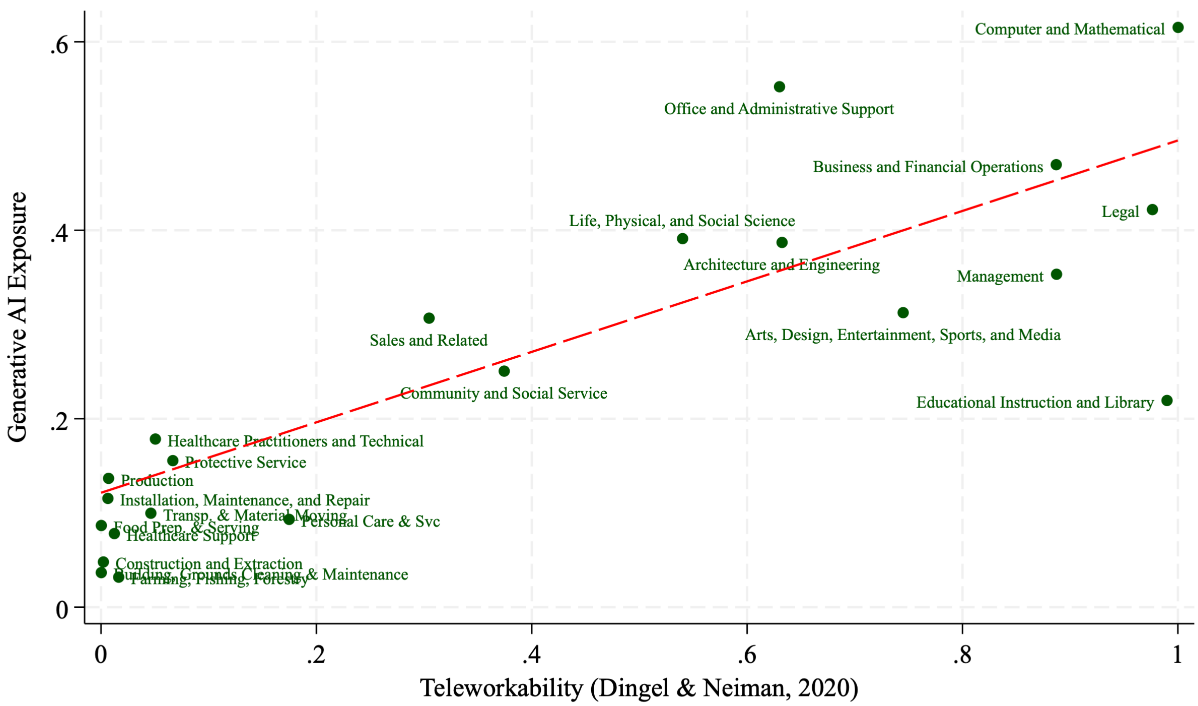


Figure 5:
Firm characteristics and remote work adoption

This figure shows OLS estimates of coefficients for the effect of standardized firm characteristics in 2019 on the firm's remote work prevalence in 2021/2022 (excl. Q4 2022) job postings in a regression of the form

$$\text{RemoteWorkShare('21-'22)}_i = \alpha_{ind} + \beta\ \text{FirmCharacteristic(2019)}_i + \text{Controls}_i + \varepsilon_i,$$

where the controls in all regressions include the 2019 value of the dependent variable as a control variable, so the coefficients can be interpreted as the effect of a standardized difference in the characteristic on changes in the remote work share. The control variables also include NAICS 2-digit fixed effects, firm-level teleworkability in 2019 and 2021/2022; and the company's share of jobs requiring a college education in 2019. The 95% confidence intervals shown are based on heteroskedasticity-robust standard errors clustered at the NAICS 2-digit sector level.

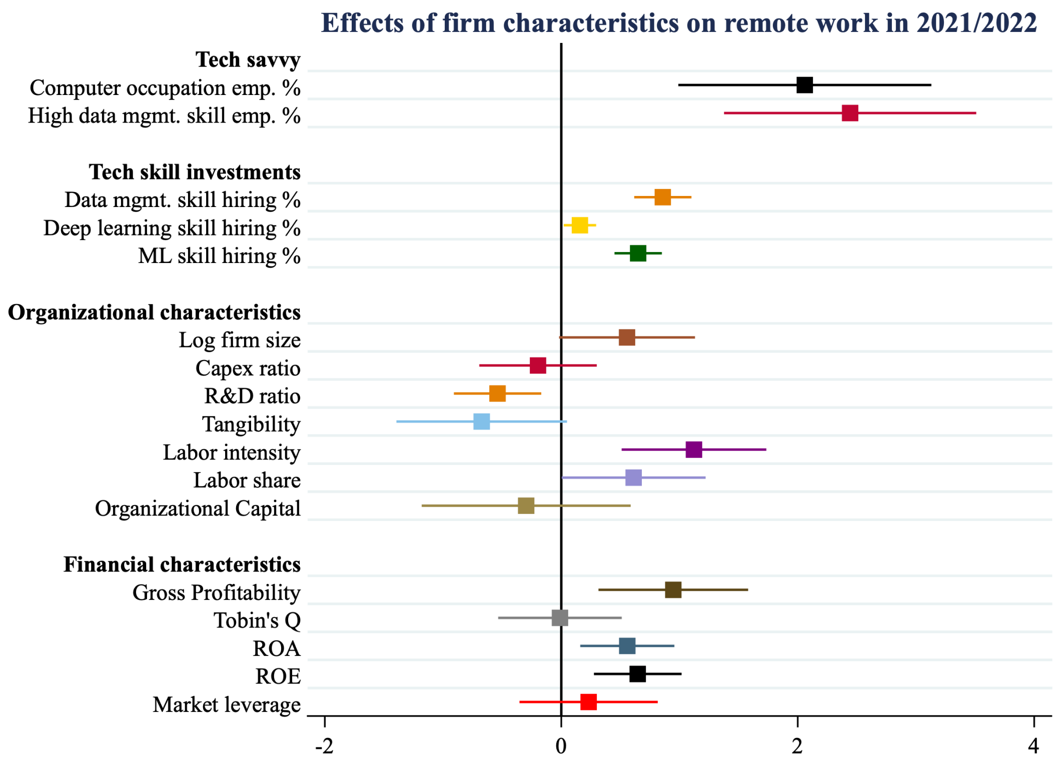


Figure 6:
Effects of remote work adoption on firm hiring characteristics

This figure shows coefficients estimated using IV for the effect of remote work prevalence in a firm's 2021/2022 (excl. Q4 2022) job postings on the standardized characteristics of the firm's job postings in 2022 in a regression of the form

$$\text{Skill}(2022)_i = \alpha + \beta \text{ RemoteWorkShare}(\text{‘21-‘22})_i + \gamma\text{Skill}(2019)_i + \text{Controls}_i + \varepsilon_i,$$

where the controls in all regressions include the standardized 2019 value of the dependent variable as a control variable, so the coefficients can be interpreted as the effect of changes in remote work shares on changes in the composition. The instrument consists of the interaction between firm-level exposure to MSA teleworkability through its hiring labor markets and firm-level teleworkability (all measured in 2019). All regressions also include the following control variables: NAICS 2-digit fixed effects; company's remote work share in 2019, the company's uninteracted exposure to MSA teleworkability in 2019, uninteracted firm-level teleworkability in 2019, the company's share of jobs requiring a college education and the share requiring an advanced degree in 2019, the share of the company's job postings in 2019 that was for computer occupations or manager positions; the log of total job postings in 2019 and in 2022; the company's labor market exposure to MSA remote shares in 2019. The 95% confidence intervals shown are based on heteroskedasticity-robust standard errors clustered at the NAICS 2-digit sector level.

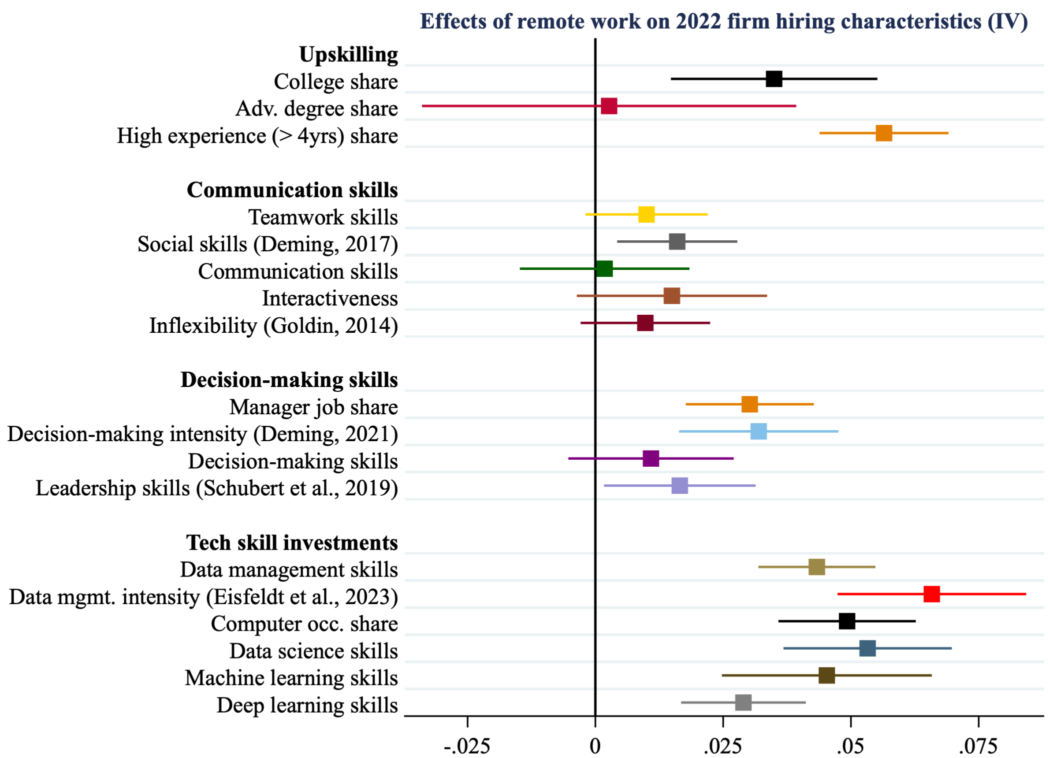


Figure 7:
Firm-level IV first-stage

This figure shows the effect of the interaction between a firm's exposure to MSA level teleworkability and firm-level teleworkability (both measured in 2019) on the horizontal axis, and the firm's job posting remote work prevalence in the YTD as of Sep. 2024 on the vertical axis. The values on both axes are residualized with regard to the uninteracted teleworkability terms.

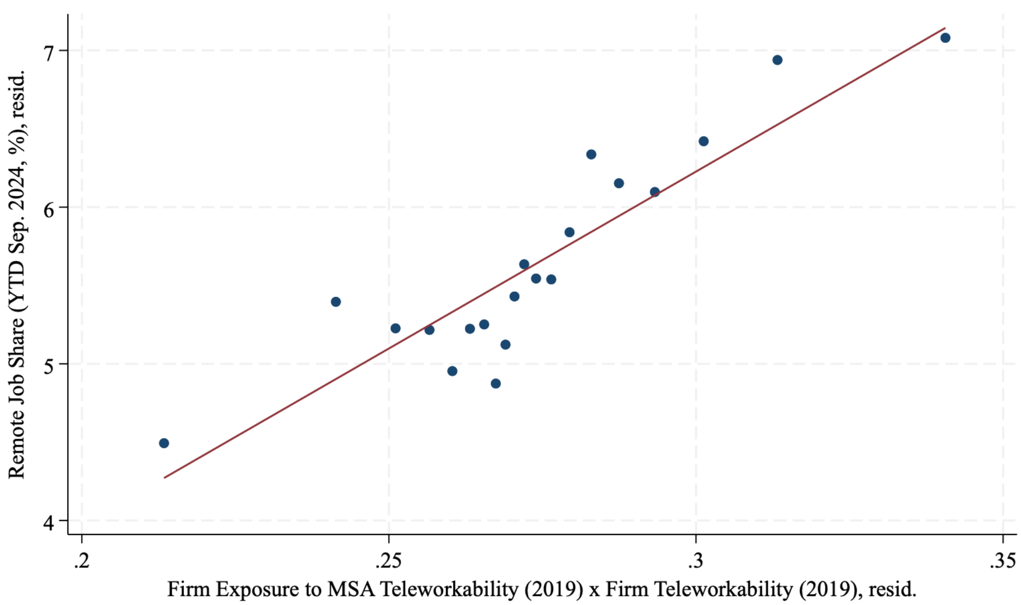
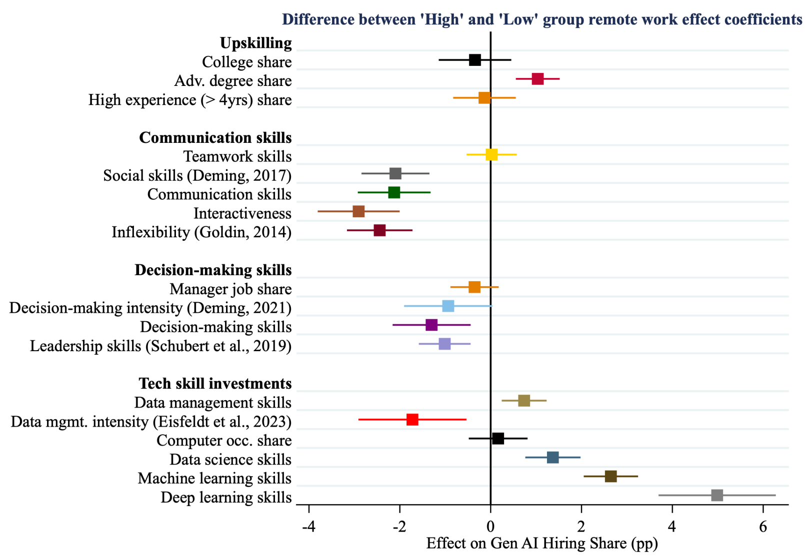


Figure 8:
Remote work effects on Gen. AI adoption by firm characteristics

This figure shows coefficients estimated using IV for the effect of remote work prevalence in a firm's 2021/2022 (excl. Q4 2022) job postings on the prevalence of generative AI mentions in a firm's job postings in 2023/2024 (excl. Q4 2024) in a regression of the form:

$$100 \times \text{GenAIJobShare(`23-`34)}_i = \alpha_{ind} + \beta \text{ RemoteWorkShare(`21-`22)}_i + \text{Controls}_i + \varepsilon_i,$$

where the dependent variable has been scaled by 100 for better readability, such that all coefficients capture 100 times the elasticity of generative AI adoption shares with regard to remote work shares. So, a coefficient of 10 indicates that a 10 pp change in remote work causes a 1pp change in generative AI adoption. High and Low groups indicate whether a firm is above or below average in the characteristic. The instrument consists of the interaction between firm-level exposure to MSA teleworkability through its hiring labor markets and firm-level teleworkability (all measured in 2019). All regressions also include the following control variables: NAICS 2-digit fixed effects; company's remote work share in 2019, the company's uninteracted exposure to MSA teleworkability in 2019, uninteracted firm-level teleworkability in 2019, the company's share of jobs requiring a college education and the share requiring an advanced degree in 2019; the company's labor market exposure to MSA remote shares in 2019; the company's teleworkability of 2023/2024 hiring, and the company's generative AI exposure in 2023/2024 hiring. The 95% confidence intervals shown are based on heteroskedasticity-robust standard errors clustered at the firm level.



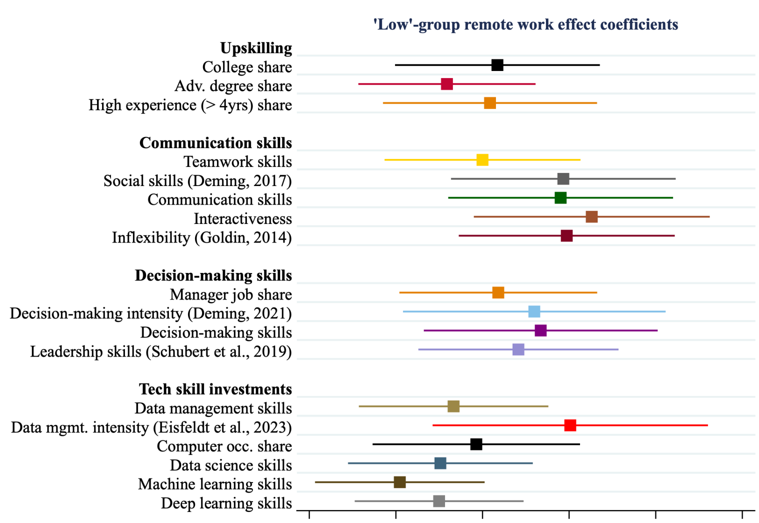


Figure 9:
Remote work trends by firm-level generative AI exposure

This figure shows the share of job postings in each quarter that are for jobs that are for remote jobs. In each panel, the jobs are aggregated into job posting-weighted quartiles of the firms' Eisfeldt et al. (2023) generative AI exposure, based on job postings in 2021-2022 (excl. Q4 2022). The grey drop line indicates the period (Q4 2022) when ChatGPT was released.

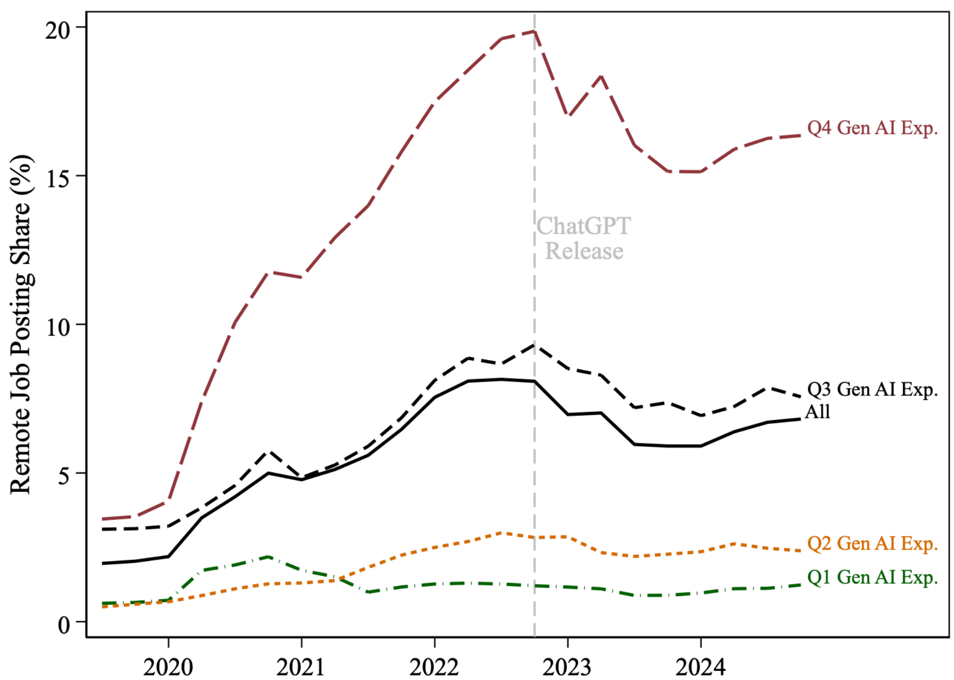
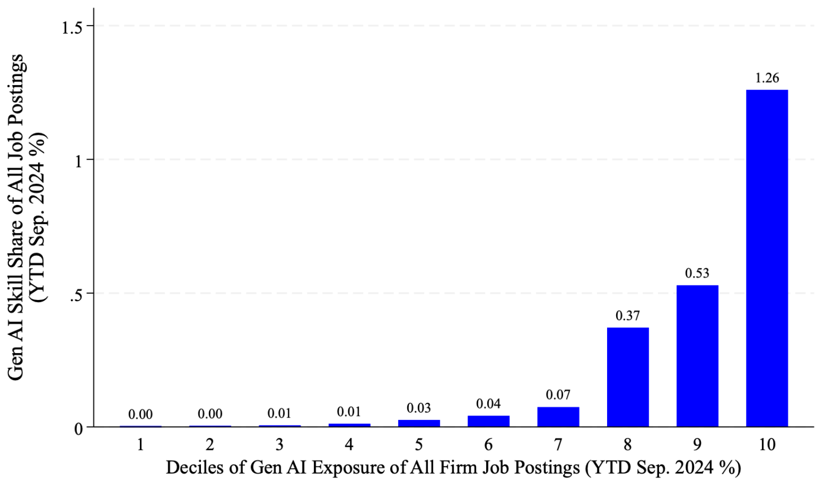
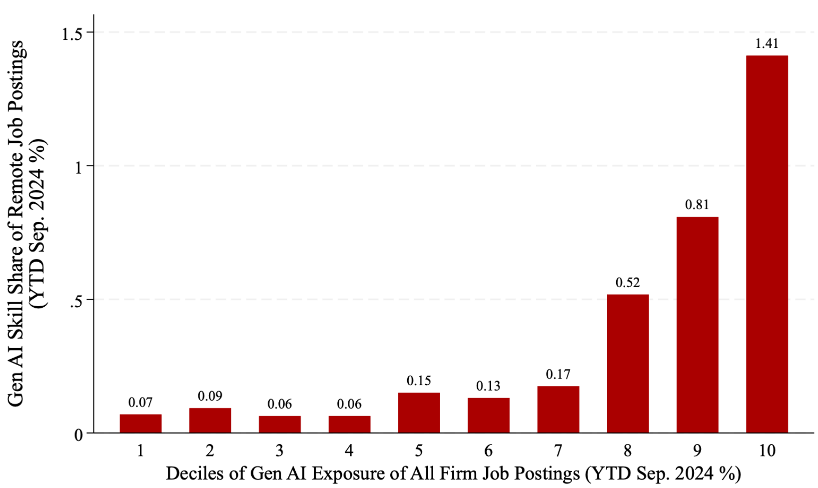


Figure 10:
Generative AI exposure and generative AI adoption by firms

These graphs show the relationship between the share of job postings at the firm level that mention generative AI skills in the YTD Sep. 2024 period, and the Eisfeldt et al. (2023) measure of generative AI exposure of the firm's job postings. In panel A the vertical axis shows the share of generative AI skill mentions in all job postings, and panel B shows the share of generative AI skill mentions only in remote job postings. In each panel, firms are sorted into deciles by exposure, weighted by total job postings and each bar shows the total job posting-weighted mean share of all (panel A) or remote (panel B) posted jobs at firms in that decile of exposure that mention generative AI.



(A) Generative AI exposure and adoption: all jobs



(B) Generative AI exposure and adoption: remote jobs

Figure 11:
Gen. AI exposure effects on Gen. AI adoption by firm characteristics

This figure shows the the synthetic diff-in-diff effect estimates of the difference between the treated and control groups in generative AI adoption after the release of ChatGPT for different subsets of firms based their hiring characteristics. The treatment group is defined as firms that are in the top decile of generative AI exposure based on the composition of their 2021/2022 job postings (excl. Q4 2022). The control group is determined by weighting firms outside the top decile to find the best fit to the pre-period trends in the treatment group, as described in Arkhangelsky et al. (2021). The subgroups are defined as firms that are above-median (top panel estimates) or below-median (bottom panel estimates) in terms of each characteristic of firm hiring in 2022. The 95% confidence intervals shown are based on block bootstrap standard errors computed from 50 resamples, using the procedure detailed in Clarke et al. (2023).

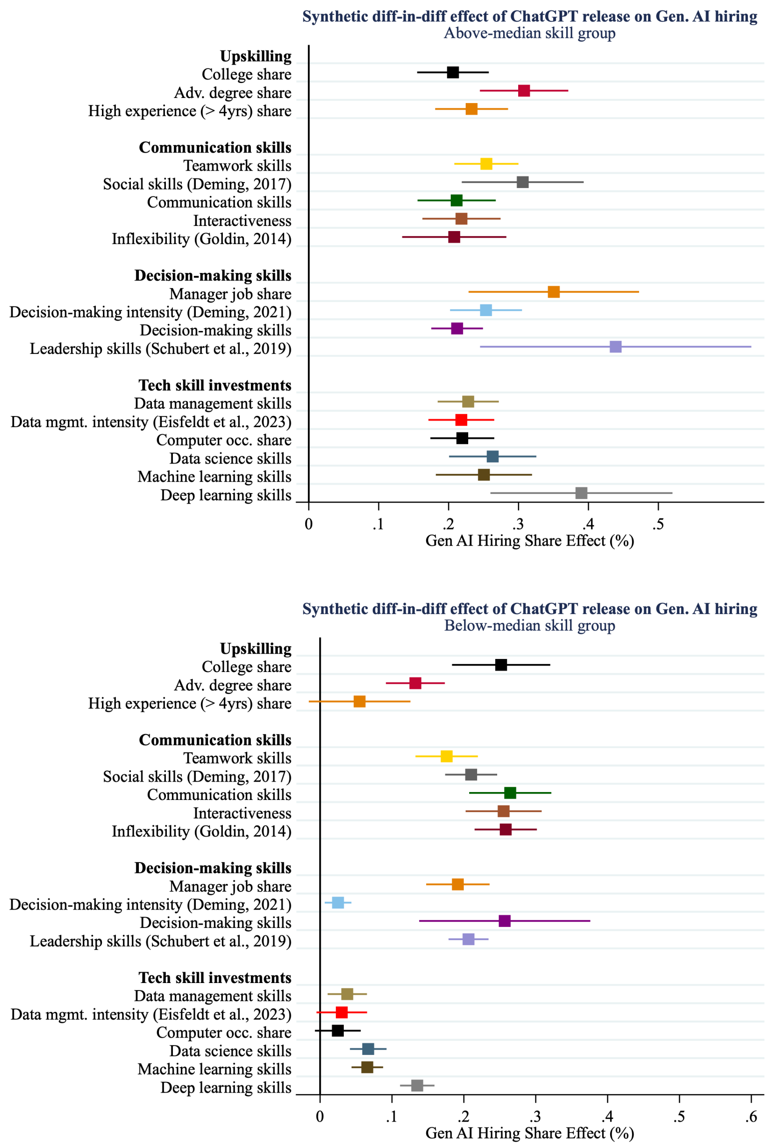
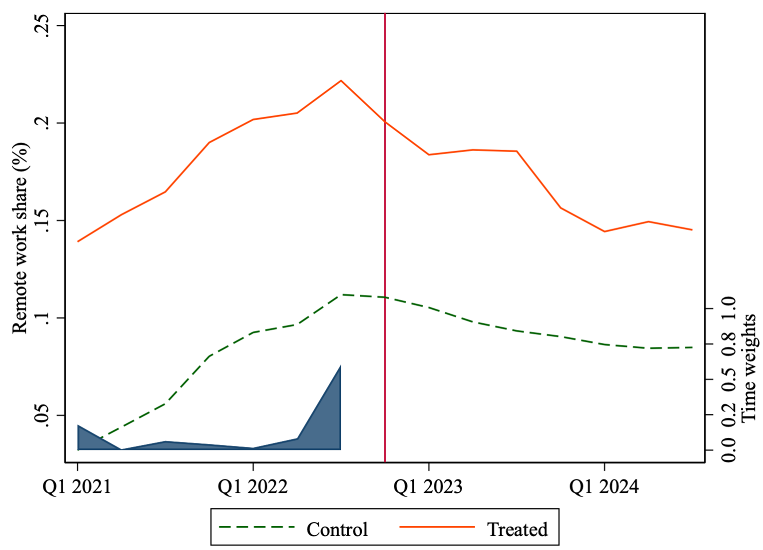
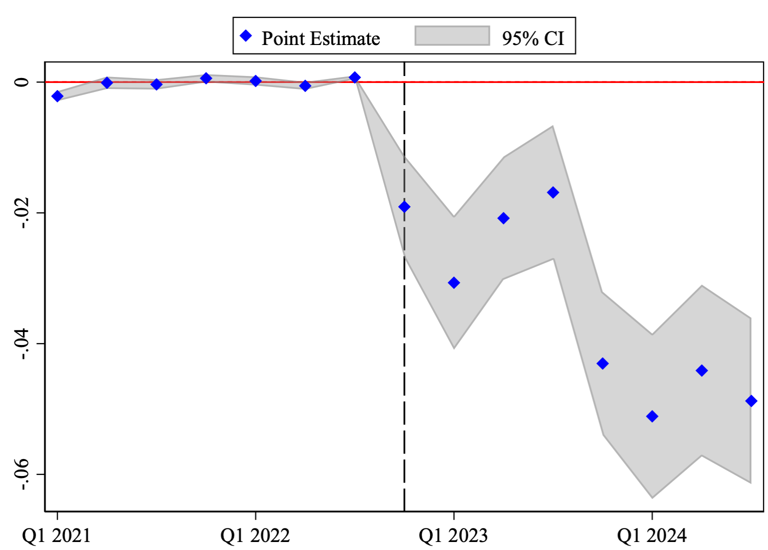


Figure 12:
Synthetic diff-in-diff event study results

These graphs show the differences in remote work share trends between the treated and control groups that underlie the synthetic diff-in-diff effect estimates reported in Table V. Panel A shows the remote work trends over time in the synthetic control group and the treatment group. The treatment group is defined as firms that are in the top decile of generative AI exposure based on the composition of their 2021/2022 job postings (excl. Q4 2022). The control group is determined by weighting firms outside the top decile to find the best fit to the pre-period trends in the treatment group, as described in Arkhangelsky et al. (2021). The right axis and the solid area in the graph shows the optimal time weights applied to different pre-periods in the estimation. Panel B shows the estimated difference in remote work shares between the control and treatment group in each quarter (blue dots), as well as the 95% confidence interval based on block bootstrap standard errors computed from 100 resamples, using the procedure detailed in Clarke et al. (2023).



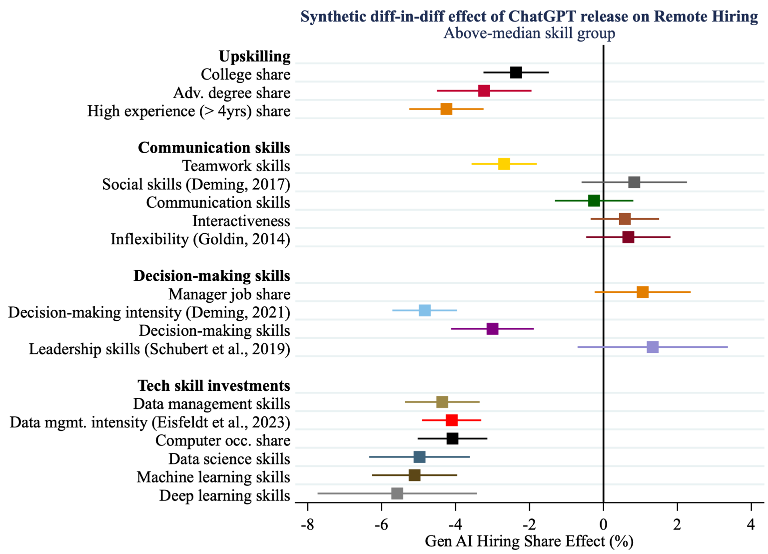
(A) Remote Work Trends: Synthetic Control vs. Treatment Group



(B) Dynamic Treatment Effects of Top Decile Gen. AI Exposure

Figure 13:
Gen. AI exposure effects on remote work by firm characteristics

This figure shows the the synthetic diff-in-diff effect estimates of the difference between the treated and control groups in remote work shares after the release of ChatGPT for different subsets of firms based their hiring characteristics. The treatment group is defined as firms that are in the top decile of generative AI exposure based on the composition of their 2021/2022 job postings (excl. Q4 2022). The control group is determined by weighting firms outside the top decile to find the best fit to the pre-period trends in the treatment group, as described in Arkhangelsky et al. (2021). The subgroups are defined as firms that are above-median (top panel estimates) or below-median (bottom panel estimates) in terms of each characteristic of firm hiring in 2022. The 95% confidence intervals shown are based on block bootstrap standard errors computed from 50 resamples, using the procedure detailed in Clarke et al. (2023).



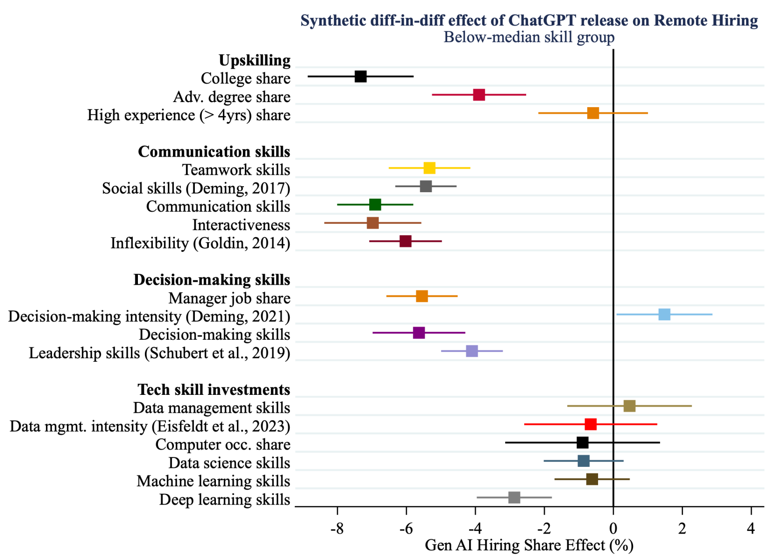


Table I:
Remote work and generative AI prevalence by occupation.

This table shows the share of all job postings in the YTD ending Sep. 2024 in each 6-digit SOC 2010 occupation that are for remote jobs (panel A), require generative AI-related skills (panel B), and are both remote and require generative AI skills (panel C). Each panel shows the top 20 occupations, ranked by the measure of interest, which have at least 5,000 job postings during the measurement period. The last column of the table shows the total job postings in the sample for that occupation.

(a) A: Remote shares

SOC	Occupation title	Remote	Jobs
15-2011	Actuaries	40	9,871
41-9041	Telemarketers	30	6,026
21-1014	Mental Health Counselors	28	60,334
27-3042	Technical Writers	28	19,584
41-3041	Travel Agents	28	5,208
13-2053	Insurance Underwriters	26	19,385
13-1031	Claims Adjusters, Examiners, and Investigators	24	58,753
43-9041	Insurance Claims and Policy Processing Clerks	23	20,677
41-9031	Sales Engineers	21	13,462
27-3043	Writers and Authors	21	27,545
19-3094	Political Scientists	20	6,688
21-1022	Healthcare Social Workers	20	25,264
15-1121	Computer Systems Analysts	20	78,807
15-1134	Web Developers	20	69,144
13-1075	Labor Relations Specialists	20	5,305
19-3031	Clinical, Counseling, and School Psychologists	19	25,873
23-1011	Lawyers	19	103,553
21-1013	Marriage and Family Therapists	19	26,145
13-1111	Management Analysts	18	125,206
15-2041	Statisticians	18	6,128

(b) B: Generative AI shares

SOC	Occupation title	Gen. AI	Jobs
15-1131	Computer Programmers	8.5	19,768
27-3042	Technical Writers	6.1	19,584
27-3043	Writers and Authors	5.8	27,545
15-2099	Mathematical Science Occupations, All Other	4	187,460
27-3091	Interpreters and Translators	3	22,998
27-3041	Editors	1.9	16,550
11-2021	Marketing Managers	1.7	197,468
15-1133	Software Developers, Systems Software	1.7	218,581
15-1132	Software Developers, Applications	1.7	218,581
11-3021	Computer and Information Systems Managers	1.4	17,145
15-1134	Web Developers	1.4	69,144
15-1141	Database Administrators	1.2	133,219
27-1011	Art Directors	1.1	9,699
43-9011	Computer Operators	1.1	305,659
27-1014	Special Effects Artists and Animators	1.1	6,281
25-9031	Instructional Coordinators	.98	28,773
25-3099	Teachers and Instructors, All Other	.95	38,229
11-9041	Architectural and Engineering Managers	.95	65,851
27-1021	Commercial and Industrial Designers	.89	18,390
15-2041	Statisticians	.78	6,128

(c) C: Generative AI share in remote jobs

SOC	Occupation title	Gen. AI ∣ Remote	Jobs
27-3091	Interpreters and Translators	21	22,998
27-3042	Technical Writers	18	19,584
15-1131	Computer Programmers	11	19,768
27-3043	Writers and Authors	9.7	27,545
27-1014	Special Effects Artists and Animators	6.4	6,281
25-9021	Farm and Home Management Educators	4.8	20,921
15-2099	Mathematical Science Occupations, All Other	3.9	187,460
17-1011	Architects, Except Landscape and Naval	3.5	9,934
25-9031	Instructional Coordinators	3.4	28,773
15-2041	Statisticians	2.9	6,128
25-2031	Secondary School Teachers, Except Special and Career/Technical Education	2.8	131,514
11-9041	Architectural and Engineering Managers	2.5	65,851
11-9032	Education Administrators, Kindergarten through Secondary	2.2	54,092
19-4021	Biological Technicians	2	7,372
29-9011	Occupational Health and Safety Specialists	2	47,336
15-1134	Web Developers	1.9	69,144
11-2021	Marketing Managers	1.6	197,468
13-1151	Training and Development Specialists	1.4	66,980
15-1132	Software Developers, Applications	1.3	218,581
15-1133	Software Developers, Systems Software	1.3	218,581

Table II:
Remote work and Gen. AI Adoption YTD Sep. 2024: Firm-level results

The instrument consists of the interaction between firm-level exposure to MSA teleworkability through its hiring labor markets and the firm's own teleworkability (measured in 2019). The control variables include proxies for the task-level teleworkability (Dingel and Neiman, 2020) and generative AI exposure (Eisfeldt et al., 2023) at the firm, 2019 remote work shares at the firm, exposure to MSA remote work levels through the firm's hiring labor markets, as well as industry sector fixed effects and the level of education required for average job postings at the firm. T-test statistics based on heteroskedasticity-robust standard errors clustered at the company level in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Dependent variable:	100 × Generative AI Job Share (%)				Remote Share (%)
Estimation:	OLS	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)
Remote Job Share (%)	0.51***	5.66***	7.31***	8.02***	
	(10.91)	(11.26)	(9.70)	(7.73)	
MSA Telew._{19} × Firm Telew._{19}					22.58***
					(12.68)
Observations	140,540	101,191	101,179	88,472	88,472
1st-stage KP F-stat.		556	287	161	
Firm remote work & telework. (2019)		X	X	X	X
Firm exposure to MSA remote work & telework. (2019)		X	X	X	X
Firm Gen. AI potential			X	X	X
Firm Teleworkability			X	X	X
Firm adv. education requirements			X	X	X
2-dig. Industry FEs				X	X

Table III:
Remote work and Gen. AI Adoption YTD Sep. 2024: Occ. × Firm-level results

The instrument consists of the interaction between firm-level exposure to MSA teleworkability through its hiring labor markets (measured in 2019) and occupation-level remote work adoption as of 2021-2022. T-test statistics based on heteroskedasticity-robust standard errors double-clustered at the company and 6-digit occupation level in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Dependent variable:	100 × Generative AI Job Share (%)			
Estimation:	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
Remote Job Share (%)	3.65***	9.35***	12.07***	17.67***
	(5.74)	(4.75)	(4.04)	(2.83)
Observations	2,166,999	2,166,992	1,953,368	2,170,436
1st-stage KP F-stat.	793	91	49	23
Firm remote work & telework. (2019)	X	X	X	
Firm exposure to MSA remote work & telework. (2019)	X	X	X	
Occupation FEs		X	X	X
Firm Gen. AI potential			X	
Firm Teleworkability			X	
2-dig. Industry FEs			X	
Firm FEs				X

Table IV:
Remote work effect on Gen. AI adoption by occupation characteristic

The instrument consists of the interaction between firm-level exposure to MSA teleworkability through its hiring labor markets (as measured in 2019) and occupation-level remote work shares in 2021-2022. T-test statistics based on heteroskedasticity-robust standard errors clustered at the company level in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Dependent variable:	100 × Generative AI Job Share (%)							
Estimation:	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)	IV (8)
Remote Job Share (%)	11.09*** (4.25)	5.36*** (4.77)	13.52*** (5.72)	14.55*** (5.31)	17.35*** (5.22)	14.51*** (5.49)	14.73*** (5.58)	14.29*** (5.31)
× 𝟙[High Job Zone]	3.01*** (5.34)							
× 𝟙[High Decision-Making]		1.59*** (3.31)						
× 𝟙[High Social Skills]			-2.53*** (-3.87)					
× 𝟙[High Coordination]				-0.40 (-0.85)				
× 𝟙[High Interaction]					-4.68*** (-4.26)			
× 𝟙[High Leadership]						-2.04*** (-3.19)		
× 𝟙[High Inflexibility]							-3.77*** (-4.42)	
× 𝟙[High Social x Analyt.]								0.30 (0.57)
Observations	2,140,024	1,618,796	2,116,418	2,116,418	2,116,418	2,116,418	2,116,418	2,116,418
1st-stage KP F-stat.	27	60	36	29	27	32	33	29
Firm FEs	X	X	X	X	X	X	X	X
Occupation FEs	X	X	X	X	X	X	X	X

Table V:
Synthetic diff-in-diff event study: remote work share effects

This table shows estimates of the effect of being in the high generative AI exposure group post-ChatGPT release, estimated using the synthetic diff-in-diff estimator in equation 7. The treatment group is defined as firms that are in the top decile of generative AI exposure based on the composition of their 2021/2022 job postings (excl. Q4 2022). The control group is determined by weighting firms outside the top decile to find the best fit to the pre-period trends in the treatment group, as described in Arkhangelsky et al. (2021). The dependent variable is the share of all jobs that mention generative AI skills in column 1, and the share of all jobs that are remote in columns 2 and 3. T-test statistics based on standard errors from a block bootstrap procedure with 50 resamples at the company level in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Dependent variable:	Share of All Jobs		
Job category:	Gen. AI (1)	Remote (2)	Remote (3)
$\mathbb{1}$[Post-ChatGPT]×$\mathbb{1}$[High Gen. AI Exposure]	0.002***	-0.034***	-0.035***
	(11.28)	(-7.00)	(-9.11)
Observations	222,555	222,555	222,555
Estimation:	SDID	SDID	SDID
Firm FEs	X	X	X
Time FEs	X	X	X
Teleworkability of firm job postings			X

Table VI:
Change in firm-level job characteristics after GenAI adoption

This table shows estimates of the effect of being in the high generative AI exposure group post-ChatGPT release, estimated using the synthetic diff-in-diff estimator in equation 7. The treatment group is defined as firms that are in the top decile of generative AI exposure based on the composition of their 2021/2022 job postings (excl. Q4 2022). The control group is determined by weighting firms outside the top decile to find the best fit to the pre-period trends in the treatment group, as described in Arkhangelsky et al. (2021). The dependent variables represent shares of different job categories among all non-remote worker (panel A) and remote worker (panel B) job postings at the firm, in each panel only including only firms that have non-remote or remote job postings, respectively, in all quarters included in the sample (Q1 2021-Q3 2024). T-test statistics based on standard errors from a block bootstrap procedure with 50 resamples at the company level in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Dep. var. job category:	Gen. AI (1)	High Experience (2)	Medium Experience (3)	Low Experience (4)	College (5)	Advanced degree (6)	Data mgmt. (7)	Decision making (8)	Commu-nication (9)
					Panel A: Share of Non-Remote Jobs				
𝟙[Post]×𝟙[High Gen. AI Exp.]	0.002***	0.017***	-0.011***	-0.004	0.005	0.000	0.003***	0.016***	0.009**
	(11.90)	(7.07)	(-4.08)	(-1.64)	(1.56)	(0.47)	(2.70)	(4.58)	(2.49)
Observations	220,980	220,980	220,980	220,980	220,980	220,980	220,980	220,980	220,980
					Panel B: Share of Remote Jobs				
𝟙[Post]×𝟙[High Gen. AI Exp.]	0.002***	0.011**	-0.012	0.001	0.005	-0.001	0.005	0.023***	0.014*
	(3.86)	(2.12)	(-1.59)	(0.09)	(0.69)	(-0.58)	(1.21)	(4.20)	(1.71)
Observations	33,900	33,900	33,900	33,900	33,900	33,900	33,900	33,900	33,900
Estimation:	SDID	SDID	SDID	SDID	SDID	SDID	SDID	SDID	SDID
Firm FEs	X	X	X	X	X	X	X	X	X
Time FEs	X	X	X	X	X	X	X	X	X

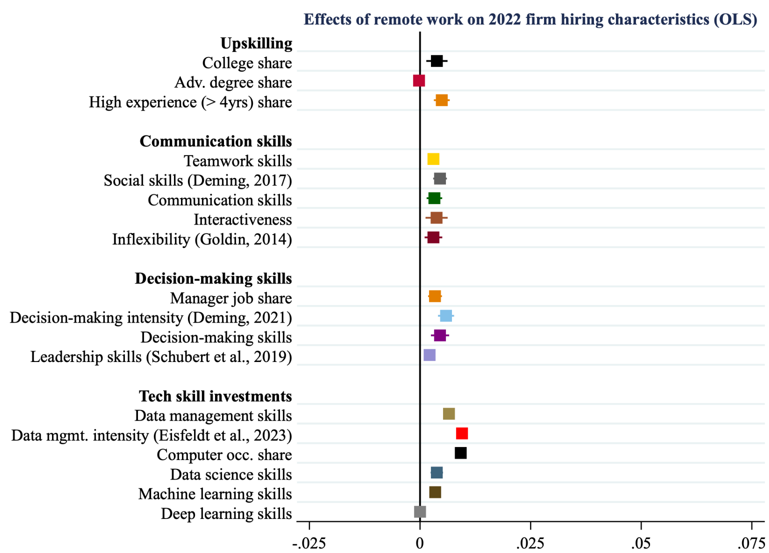
Appendix A. Appendix Figures

Figure 14:
Effects of remote work adoption on firm hiring characteristics (OLS)

This figure shows coefficients estimated using OLS for the effect of remote work prevalence in a firm's 2021/2022 (excl. Q4 2022) job postings on the standardized characteristics of the firm's job postings in 2022 in a regression of the form

$$\text{Skill(2022)}_i = \alpha + \beta \text{ RemoteWorkShare('21-'22)}_i + \gamma \text{Skill(2019)}_i + \text{Controls}_i + \varepsilon_i,$$

where the controls in all regressions include the standardized 2019 value of the dependent variable as a control variable, so the coefficients can be interpreted as the effect of changes in remote work shares on changes in the composition. All regressions also include the following control variables: NAICS 2-digit fixed effects; company's remote work share in 2019, the company's uninteracted exposure to MSA teleworkability in 2019, uninteracted firm-level teleworkability in 2019, the company's share of jobs requiring a college education and the share requiring an advanced degree in 2019, the share of the company's job postings in 2019 that was for computer occupations or manager positions; the log of total job postings in 2019 and in 2022; the company's labor market exposure to MSA remote shares in 2019. The 95% confidence intervals shown are based on heteroskedasticity-robust standard errors clustered at the NAICS 2-digit sector level.



Appendix B. Derivations

Appendix A. Optimal decision-making intensity

Maximizing the expression in equation 1 with regard to D_f, the firm's first-order condition is

$$\frac{j-k_{fj}}{1-D_f} = \frac{\eta(e^j - e^{k_{fj}})}{\eta D_f + \rho^{\mathbb{1}[\text{Remote}]} M_f},$$

where the LHS captures the cost in terms of lost output of spending more time on decisions, while the RHS represents the benefit in terms of additional quality of decisions for the firm's tasks. Some algebra then results in the optimal decision intensity as

$$D_f^* = \frac{(e^j - e^{k_{fj}}) - \frac{1}{\eta}(j-k_{fj})\rho^{\mathbb{1}[\text{Remote}]} M_f}{(e^j - e^{k_{fj}}) + (j-k_{fj})}$$

which is the expression in equation2.

Appendix B. Remote work decision quality.

Starting from the optimal decision intensity

$$D_f^* = \frac{(e^j - e^{k_{fj}}) - \frac{1}{\eta}(j-k_{fj})\rho^{\mathbb{1}[\text{Remote}]} M_f}{(e^j - e^{k_{fj}}) + (j-k_{fj})},$$

note that this can be written as

$$D_f^* = \frac{(e^j - e^{k_{fj}})}{(e^j - e^{k_{fj}}) + (j-k_{fj})} - \frac{(j-k_{fj})}{\eta((e^j - e^{k_{fj}}) + (j-k_{fj}))}\rho^{\mathbb{1}[\text{Remote}]} M_f.$$

As decision quality is defined as

$$Q_{fj} = \ln\left(\eta D_f + \rho^{\mathbb{1}[\text{Remote}]} M_f\right),$$

it follows that the sign of the change in overall decision quality with regard to changes in central decision support is the same as the sign of

$$1 - \frac{(j-k_{fj})}{(e^j - e^{k_{fj}}) + (j-k_{fj})},$$

such that

$$\frac{\partial Q_{fj}}{\partial(\rho^{\mathbb{1}[\text{Remote}]} M_f)} > 0 \Leftrightarrow e^j - e^{k_{fj}} > 0.$$

That is, as long as the decision quality has a positive effect on output, then an increase in central decision support is not going to be fully offset by a reduction in local decision intensity. This implies that *remote firms have lower overall decision quality even though they invest more worker effort in local decisionmaking*