Organizational Technology Ladders: Remote Work and Generative AI Adoption

Gregor Schubert

UCLA Anderson *

December 16, 2024

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 provide evidence that remote work and generative AI adoption are connected - they occur in the same firms and their time trends suggest that they affect one another. 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, the rise of remote work reverses after ChatGPT is released. I provide evidence from a synthetic difference-in-differences estimate that firms that were more exposed to generative AI technology reduced their demand for remote workers after generative AI technology became salient. I provide a conceptual framework for understanding these results based on "organizational technology ladders" where investing in one technology makes it easier for an organization to adopt the other, and where technologies can coincide and substitute for one another in the same tasks and jobs, such that technological waves can interfere in multiple ways.

*Email: gregor.schubert@anderson.ucla.edu. Website: https://sites.google.com/view/gregorschubert.

"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)

Most recently, the Covid pandemic has tested the resilience of cities, firms and society at large to broad shifts in technology and social preferences (Glaeser and Cutler, 2022). 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 wave of technology shocks. 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). However, these potential productivity increases are unevenly distributed, affecting higher-wage occupations to a larger degree. While there is some evidence that, in the short run, firms have on average responded by reducing hiring in the most exposed occupations (Eisfeldt, Schubert, Zhang, and Taska, 2023), whether this new technology complements or substitutes for particular jobs is likely to vary not just across occupations but also depends on the local labor market context and existing firm capabilities, including previous technology investments.

In this study, I show that these large shocks to organizational technology—remote work and generative AI—are not separate phenomena. To the contrary, remote work and generative AI are intimately connected in their effect on firms and workers, and studying them jointly reveals new insights regarding how firms are impacted by, and adapt to, these shocks.

Intuitively, there may be both positive and negative mutually reinforcing effects between remote work and generative AI: these technologies may have larger impacts on similar tasks and organizations due to the fundamental nature of the underlying technological changes. At the same time, adoption of the earlier technology may make it easier for firms to incorporate the next technology, as they might rely on similar infrastructure and organizational or human capital investments. Moreover, one technology may directly affect the cost of adopting the other. For instance, remote work produces a digital trail of data that can be used to train generative AI models to automate the associated tasks, and often establishes asynchronous work and automatic quality control processes that ease the introduction of generative AI tools that require a similar work context. Conversely, generative AI facilitates decentralized analysis and easier communication for some remote workers (e.g. through automatic note-taking and semantic searches of knowledge databases). These interactions could lead to one technology complementing or substituting for the adoption of the other, depending on the exact form that these interactions take.

In this paper, I quantify the empirical direction and size of this interaction between remote jobs and generative AI using detailed occupation-by-firm job posting data to estimate 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 understand how these technologies interact, 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) Generative AI adoption rates are much higher and rising more steeply among remote workers. (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 the two technologies are likely to interact, compounding or mitigating 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, to evaluate which aspects of remote work might affect later generative AI adoption, I explore how remote work adoption changes the skill mix of firms. 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 remote work adoption during the pandemic causes firms to "upskill", increasing demand for higher-skilled occupations and college-educated workers. Moreover, remote work caused firms to demand greater decision-making and communication skills from non-remote workers, while increasing the need for data management skills in all hiring.

Third, I establish that remote work had a causal effect on firms' ability to adopt generative AI tools: using the same IV design, I find that remote work causes greater generative AI skill demand in firms' job postings by 2024, even when controlling for detailed measures of firms' pre-existing exposure to remote work and exposure to generative AI, or firm and occupation fixed effects. These effects are stronger within firms for occupations that require more decision-making skills and experience, and fewer social skills, interaction, and direct leadership of others.

Fourth, I use a synthetic difference-in-differences design following Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021) to estimate the effect of greater generative AI exposure on remote work prevalence in firm hiring after the release of ChatGPT. I find that, 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 event study estimates also show that higher generative AI exposure caused firms to further move towards upskilling both their remote and non-remote hiring, and to further increase the importance of decision-making skills in their hiring.

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. This path dependency can mitigate or exacerbate differences in productivity among firms and labor market outcomes among workers that result from technology shocks. Collectively, the findings in this paper show that the two biggest technological changes in firms' work processes during the last decade should be studied jointly.

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, Bloom, and Davis (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.

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

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 VI. I reverse the direction of analysis by estimating the effect of generative AI adoption on remote work prevalence in Section VII. Finally, Section VIII 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.

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 number 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 1 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 1 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 2. 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

[INCOMPLETE]

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, to invest 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.

In theory, the effects of remote work on generative AI adoption are 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 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 overseas personnel), 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

There are thus 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 and workflows, data processing capacity, quality review processes, and data on task outputs that result from implementing a remote work-friendly organization, all 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 process 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.

Only the first and second channel represent causal effects in the sense that exogenous variation in remote work adoption would also lead to variation in Generative AI adoption. As this is the causal channel that we need to quantify in order to understand to what degree

the pandemic-induced increase in remote work contributed to the generative AI boom that followed, I will first focus on trying to identify the magnitude of this causal effect. However, the channels related to particular task or firm characteristics easing the application of both remote work processes and generative AI tools in a job may be of independent policy interest and may also represent an omitted variable bias concern in a naïve estimation of the causal effect of remote work on generative AI skill demand, as I discuss in the empirial approach section.

IV. Empirical Approach

I want to estimate the effect β of having a greater share of remote jobs on firms investing in generative AI skills. This effect is estimated from regressions of the form

$$GenAIJobShare_i = \alpha + \beta RemoteJobShare_i + Controls_i + \varepsilon_i, \tag{1}$$

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.

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 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 et al. (2023). Figure 3, Panel A, shows that there is a positive relationship between occupations having tasks that are remote work suitable and tasks that are exposed to generative AI capabilities. Panel B shows that these tasks also tend to cluster in similar geographic locations, with large MSAs like Washington DC, San Francisco, Boston, or Seattle having high average teleworkability and also high generative AI exposure based on the occupational composition of their local labor markets.

Another concern arises from industry- or firm-level differences in the ability and willing-

ness 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.

Instruments. To identify exogenous variation in the remote job share, 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, 2024a), 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 variation at the firm of interest, the *average 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 compositions in different locations, firms and occupations, and exogenous national trends in remote work before generative AI technology as salient and are therefore unlikely to be correlated with endogenous generative AI adoption choices by a firm. The exclusion restriction requires that firms do not deliberately choose to hire for jobs that were unobservably more likely to see generative AI adoption in labor markets that were more likely to adopt remote work during Covid, holding constant teleworkability and task-level generative AI exposure of the firm, as well as fixed effects for average differences across firms or occupations.

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. We need a firm-by-occupation sample to study the latter questions, such that we can identify differences in effects across occupations within the same firm.

V. Remote Work Impact on Skills

In this section, I first explore how the adoption of remote work changed the hiring patterns with regard to skills among the affected firms. This provides insights into the way that work processes and firms' use of human capital are changing in response to the adoption of the technology. I estimate specifications of the form

$$\text{SkillShare}(\text{`21-`22})_i = \alpha + \beta \text{RemoteWorkShare}(\text{`21-`22})_i + \gamma \text{SkillShare}(\text{`19})_i + Controls_i + \varepsilon_i, \tag{2}$$

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. Table II shows the results at the firm level, while Table III shows the firm-by-occupation level results that allow me to control for both firm and occupation fixed effects.

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 firm-level results are shown in columns (1)-(4) of Table II: panel A shows 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, but decrease their hiring of entry-level workers. Panel B shows that these effects hold even more strongly for the composition of remote jobs at the affected firms. The corresponding columns in Table III show that these effects are similar across occupations *within* firms, except for entry-level workers, where there is also a rise within occupations, suggesting that part of the decline in entry level hiring at the firm level is due to a shift in

the composition of the firm's workforce, rather than a change in hiring within occupations. Overall, these results show that firm are *upskilling* their hiring in response to a greater remote work share.

Job skills. In columns (5)-(7) of both tables, I consider how the mentions of particular skills in job postings 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. The results show that the firm shifts its hiring away from communication skill intensive roles and towards roles that require decision-making or data management skills. The results in panel B of Table II show that the increased demand for data management skills and shift away from communication skills are particularly pronounced among the remote positions, while the increased demand for decision-making skills stems from non-remote role hiring. Table III shows that the decline in demand for communication skills is driven by a change in the composition of roles hired for: accounting for variation across occupations within a firm, the particular occupations that are going remote are requiring both more decision-making and more communication skills, which means that the firm-level results are explained by reducing hiring for occupations that are normally associated with those skills, even while demanding more of them from the occupations that are being hired remotely.

The next section estimates the consequences of the greater prevalence of remote work for generative AI adoption.

VI. Remote Work Impact on Generative AI Adoption

In this section, I estimate 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.

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 4 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 IV, column (5) for the first-stage coefficient including the full set of control variables). This strong relationship is reflected in the first-stage Kleibergen-Paap F-statistics, which are reported in all IV estimation tables, and are consistently large, suggesting a strong

instrument.

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 1. and the results are shown in Table IV. 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 V 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 IV, 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.

A. Heterogeneity of remote work effects on generative AI

In this section, I estimate whether particular occupation characteristics are associated with higher or lower impacts of remote work adoption on generative AI adoption. 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 (2024b). "High" indicators for all measures other than job zones and decision-making indicate that occupations are above the job posting-weighted average for the measure.

I interact the remote job share with indicators of high or low values of particular characteristics in an occupations, which are measured at the national level using O*Net data. The results, shown in Table VI show that the impact is larger 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 high skilled and require decision-making (which tend to be highly exposed to generative AI productivity improvements according to Eisfeldt et al. (2023)), but less so in jobs that require a lot of interaction in different forms. That is, analytically demanding roles that have less complex relationships with other people inside or outside the organization are more likely to see generative AI technology adoption. As I showed earlier, this aligns closely with the roles that proliferate within firms in response to remote work adoption.

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

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.

VII. 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 1, 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 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 1, but for firms. In Figure 5, 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 dif-

ferential 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

$$\text{RemoteWorkShare}_{it} = \mu + \alpha_i + \gamma_t + \tau \mathbb{1}[\text{Post-ChatGPT}]_t \times \mathbb{1}[\text{High Gen. AI Exposure}]_i + \beta' X_{it} + \varepsilon_{it}, \tag{3}$$

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

$$\left(\widehat{\tau}, \widehat{\mu}, \widehat{\alpha}, \widehat{\gamma}\right) = \underset{\tau,\mu,\alpha,\gamma}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\text{RemoteWorkShare}_{it} - \mu - \alpha_i - \gamma_t - \text{Treated}_{it}\tau\right)^2 \widehat{\omega}_i^{\text{sdid}}\, \widehat{\lambda}_t^{\text{sdid}} \right\} \tag{4}$$

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).[3]

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 6 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, controlling for 2-digit industry fixed effects. As the figures show, there is highly significant positive relationship 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 VII 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 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 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

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

VII 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.

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 4, 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 remote work skill composition results are shown in Table VIII and those for the non-remote work skill composition in Table IX.

Table VIII shows in column 1 that the change in the share of generative AI skills in remote work jobs is very similar to that in all 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 it coincides with an upskilling the experience distribution, shifting demand away from workers with 3-4 years of 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 across Tables VIII and IX that generative AI adoption increases demand for decision-making skills (column 8 in both) among all workers, and als evidence for an increase in communication skills, particularly among non-remote workers (column 9 in both), while demand for data management skills among remote workers is unaffected, but increased among non-remote workers (column 7 in both).

VIII. 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. In Table II I found 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 only among *non-remote* workers, while reducing demand for communication-intensive roles across all hiring. This is consistent with remote work forcing firms to substitute automatic tracking and digital work processes that require data management for direct in-person supervision and interactions. Moreover, the rise in demand for decision-making skills among non-remote workers is consistent with the increased demands on managers as a result of a reduced ability to train and supervise remote workers.

Contrasting these firm-level results with the findings in Table III that control for occupation-level differences in these characteristics shows that the decline in demand for communication skills was due to a shift in hiring composition away from communication-intensive roles, while the demand for communication within a given role actually increased in response to remote work, in line with firms responding to the difficulty of communicating remotely by reducing the need for it at the extensive margin of roles being hired for and demanding that workers in the remaining roles have greater communication skills. Similarly, the increase in demand for college-educated workers and decision-making is even more pronounced once occupation-level effects are controlled for, which suggests that firms were shifting their hiring composition away from roles that normally require decision-making and college degrees but were increasing their demands for these skills in the roles that they continued to hire for - suggesting that remote work adoption required an upskilling of the remaining workers, even while the organization as a whole adapted by reducing the amount of skilled work happening. This is consistent with firms responding to a greater difficulty of communicating and centralized decision-making by reducing the hiring in positions that are dependent on these skills, and increasing demand for these skills for a broader range of workers in other roles—in effect decentralizing these abilities within the firm.

This finding is 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).

Second, remote work 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

following the release of ChatGPT in November 2022. 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, the organizational shifts in response to remote work technology further increase the match between what workers do in the firms in question and in which tasks generative AI tools can be useful.

Third, 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 technology use further propels the upskilling of firms' hiring as generative AI tools and shift the composition of remote workers towards even mode decision-making skills as generative AI tools complement human ability to structure and evaluate analytical work output. While this ostensibly conflicts with findings in the remote work literature that within particular occupations lower-skilled workers see larger productivity benefits from using generative AI tools (e.g. Brynjolfsson et al. (2023)), these results are consistent if a low revenue elasticity with regard to price means that higher productivity of low-skilled workers using generative AI tools leads to a reduction in employment as the same output can now be produced by fewer employees.

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 cumulate 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.

REFERENCES

Akan, Mert, Jose Maria Barrero, Nicholas Bloom, Tom Bowen, Shelby Buckman, Steven J. Davis, Luke Pardue, and Liz Wilkie, 2024, Americans now live farther from their employers, Unpublished manuscript.

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens, and Stefan Wager, 2021, Synthetic difference-in-differences, *American Economic Review* 111, 4088–4118.

Bao, Lingfeng, Tao Li, Xin Xia, Kaiyu Zhu, Hui Li, and Xiaohu Yang, 2022, How does working from home affect developer productivity?—a case study of baidu during the covid-19 pandemic, *Science China Information Sciences* 65, 142102.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis, 2021, Why working from home will stick, Technical report, National Bureau of Economic Research.

Barrero, José María, Nicholas Bloom, and Steven J Davis, 2023, The evolution of work from home, *Journal of Economic Perspectives* 37, 23–49.

Bloom, Nicholas, Ruobing Han, and James Liang, 2024, Hybrid working from home improves retention without damaging performance, *Nature* 1–6.

Boeri, Filippo, Riccardo Crescenzi, and Davide Rigo, 2024, Work from home and firm productivity: The role of ict and size, Working paper, The London School of Economics.

Brynjolfsson, Erik, Danielle Li, and Lindsey R Raymond, 2023, Generative ai at work, Technical report, National Bureau of Economic Research.

Choudhury, Prithwiraj, Cameron Foroughi, and Barbara Larson, 2024, Work from anywhere: The productivity effects of geographic flexibility, *Strategic Management Journal* 45, 356–375.

Clarke, Damian, Daniel Pailanir, Susan Athey, and Guido Imbens, 2023, On synthetic difference-in-differences and related estimation methods in stata, *Stata Journal* .

Davis, Morris A, Andra C Ghent, and Jesse Gregory, 2024, The work-from-home technology boon and its consequences, *Review of Economic Studies* rdad114.

Deming, David J, 2017, The growing importance of social skills in the labor market, *The quarterly journal of economics* 132, 1593–1640.

Deming, David J, 2021, The growing importance of decision-making on the job, Technical report, National Bureau of Economic Research.

Dingel, Jonathan I, and Brent Neiman, 2020, How many jobs can be done at home?, *Journal of Public Economics* 189, 104235.

Eisfeldt, Andrea L, and Gregor Schubert, 2024, Ai and finance, Technical report, National Bureau of Economic Research.

Eisfeldt, Andrea L, Gregor Schubert, Miao Ben Zhang, and Bledi Taska, 2023, The labor impact of generative ai on firm values, *Available at SSRN 4436627* .

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock, 2023, Gpts are gpts: An early look at the labor market impact potential of large language models, *arXiv preprint arXiv:2303.10130* .

Emanuel, Natalia, and Emma Harrington, 2024, Working remotely? selection, treatment, and the market for remote work, *American Economic Journal: Applied Economics* 16, 528–559.

Frey, Carl Benedikt, and Michael Osborne, 2024, Generative ai and the future of work: a reappraisal, *Brown Journal of World Affairs* 30.

Gibbs, Michael, Friederike Mengel, and Christoph Siemroth, 2023, Work from home and productivity: Evidence from personnel and analytics data on information technology professionals, *Journal of Political Economy Microeconomics* 1, 7–41.

Glaeser, Edward, and David Cutler, 2022, *Survival of the City: The Future of Urban Life in an Age of Isolation* (Penguin).

Goldin, Claudia, 2014, A grand gender convergence: Its last chapter, *American economic review* 104, 1091–1119.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh, 2022a, Flattening the curve: pandemic-induced revaluation of urban real estate, *Journal of Financial Economics* 146, 594–636.

Gupta, Arpit, Vrinda Mittal, and Stijn Van Nieuwerburgh, 2022b, Work from home and the office real estate apocalypse .

Kogan, Leonid, Dimitris Papanikolaou, Lawrence DW Schmidt, and Bryan Seegmiller, 2023, Technology and labor displacement: Evidence from linking patents with worker-level data, Technical report, National Bureau of Economic Research.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger, 2023, The value of working conditions in the united states and implications for the structure of wages, *American Economic Review* 113, 2007–2047.

Mondragon, John A, and Johannes Wieland, 2022, Housing demand and remote work, Technical report, National Bureau of Economic Research.

Noy, Shakked, and Whitney Zhang, 2023, Experimental evidence on the productivity effects of generative artificial intelligence, *Available at SSRN 4375283* .

Powell, David, and Jeffrey B. Wenger, 2024, Workplace amenities and the costs to firms in the united states, Working paper, RAND Corporation.

Schubert, Gregor, Anna Stansbury, and Bledi Taska, 2024a, Employer concentration and outside options, *Available at SSRN 3599454* .

Schubert, Gregor, Anna Stansbury, and Bledi Taska, 2024b, Employer concentration and outside options, *Available at SSRN 3599454* .

Yang, Longqi, David Holtz, Sonia Jaffe, Siddharth Suri, Shilpi Sinha, Jeffrey Weston, Connor Joyce,

Neha Shah, Kevin Sherman, Brent Hecht, et al., 2022, The effects of remote work on collaboration among information workers, *Nature human behaviour* 6, 43–54.

Figures and Tables

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 2021-2022 and Changes in Firm-level Hiring Composition

The dependent variables measure the composition of a firm's job postings, in percent, in 2021-2022 (excl. Q4 2022). Each regression controls for the 2019 value of the dependent variable, and of the remote work share in 2019, 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 occupation-level teleworkability (all measured in 2019). 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 2021-2022:	Min. Education (%)		Min. Experience (%)		Skill share (%)		
Category:	College	Advanced degree	>4 yrs	<3 yrs	Data mgmt.	Decision making	Commu-nication
	(1)	(2)	(3)	(4)	(5)	6)	(7)
Panel A: All Jobs (Remote & Non-remote)							
Remote Job Share 2021-2022 (%)	0.73***	0.04	1.06***	-0.93***	0.38***	0.22***	-0.27***
	(9.26)	(1.62)	(15.70)	(-11.39)	(13.77)	(2.76)	(-3.00)
Observations	158,076	158,076	158,076	158,076	158,076	158,076	158,076
1st-stage KP F-stat.	472	500	469	497	448	496	505
Panel B: Remote Jobs Only							
Remote Job Share 2021-2022 (%)	0.41	-0.10	2.37***	-1.98***	1.15***	-0.38	-1.66**
	(0.74)	(-0.50)	(2.96)	(-2.78)	(2.76)	(-0.73)	(-2.42)
Observations	14,357	14,357	14,357	14,357	14,357	14,357	14,357
1st-stage KP F-stat.	12	12	12	12	12	12	12
Estimation:	IV	IV	IV	IV	IV	IV	IV
	Addl. controls & fixed effects						
Firm remote work & telework. (2019)	X	X	X	X	X	X	X
Firm exposure to MSA remote work & telework. (2019)	X	X	X	X	X	X	X
Firm Teleworkability '21-'22	X	X	X	X	X	X	X
2-dig. Industry FEs	X	X	X	X	X	X	X
Lagged dep. var. (2019)	X	X	X	X	X	X	X

Table III:
Remote Work 2021-2022 and Changes in Firm-Occ-level Hiring Composition

The dependent variables measure the composition of a firm's job postings in each occupation (measued as a 6-digit SOC 2010 code), in percent, in 2021-2022 (excl. Q4 2022). Each regression controls for the 2019 value of the dependent variable, and of the firm-by-occupation remote work share in 2019, 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 (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 2021-2022:	Min. Educat. (%)		Min. Exper. (%)		Skill share (%)		
Category:	College	Advanced degree	>4 yrs	<3 yrs	Data mgmt.	Decision making	Commu-nication
	(1)	(2)	(3)	(4)	(5)	6)	(7)
Remote Job Share 2021-2022 (%)	2.87***	-0.16	0.82***	1.07***	0.39**	2.83***	2.10***
	(3.68)	(-1.58)	(2.94)	(2.99)	(2.44)	(3.80)	(3.65)
Observations	376,033	376,033	376,033	376,033	376,033	376,033	376,033
1st-stage KP F-stat.	16	17	16	17	17	16	17
Estimation:	IV	IV	IV	IV	IV	IV	IV
Addl. controls & fixed effects							
Firm × Occ. remote work % (2019)	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X
Occupation FEs	X	X	X	X	X	X	X
Lagged dep. var. (2019)	X	X	X	X	X	X	X

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

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 V:
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 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	IV	IV	IV
	(1)	(2)	(3)	(4)
Remote Job Share (%)	3.65***	9.35***	12.07***	17.67***
	(29.68)	(9.53)	(7.79)	(5.65)
Observations	2,166,999	2,166,992	1,953,368	2,170,436
1st-stage KP F-stat.	10,990	280	138	54
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 VI:
Gen AI Adoption Heterogeneity 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***	5.36***	13.52***	14.55***	17.35***	14.51***	14.73***	14.29***
	(4.25)	(4.77)	(5.72)	(5.31)	(5.22)	(5.49)	(5.58)	(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 VII:
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 4. 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	Remote	Remote
	(1)	(2)	(3)
𝟙[Post-ChatGPT]×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 VIII:
Synthetic diff-in-diff event study: remote work characteristics

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 4. 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 remote worker job postings at the firm, including only firms that have remote job postings 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.

Dependent variable:	Share of Remote Jobs								
Job category:	Gen. AI	High Experience	Medium Experience	Low Experience	College	Advanced degree	Data mgmt.	Decision making	Commu-nication
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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

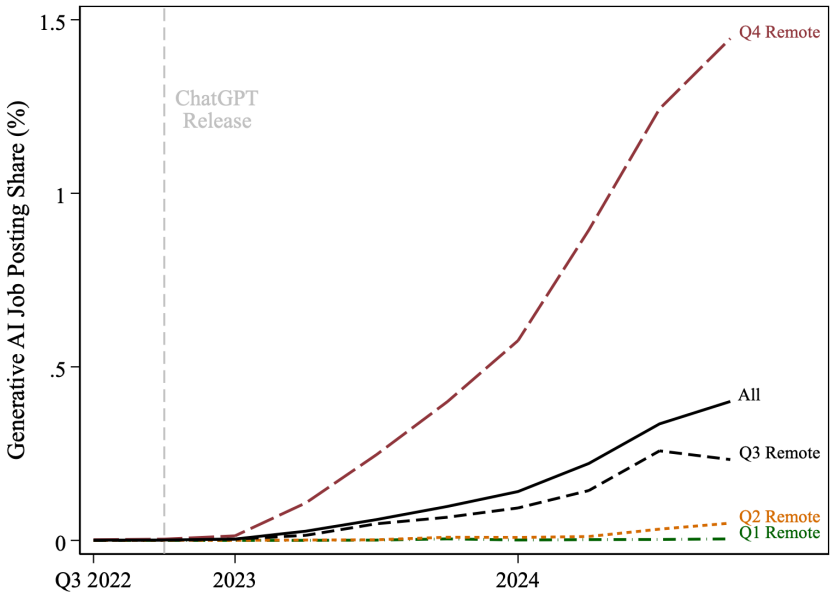
Table IX:
Synthetic diff-in-diff event study: non-remote work characteristics

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 4. 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 job postings at the firm, including only firms that have non-remote job postings 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.

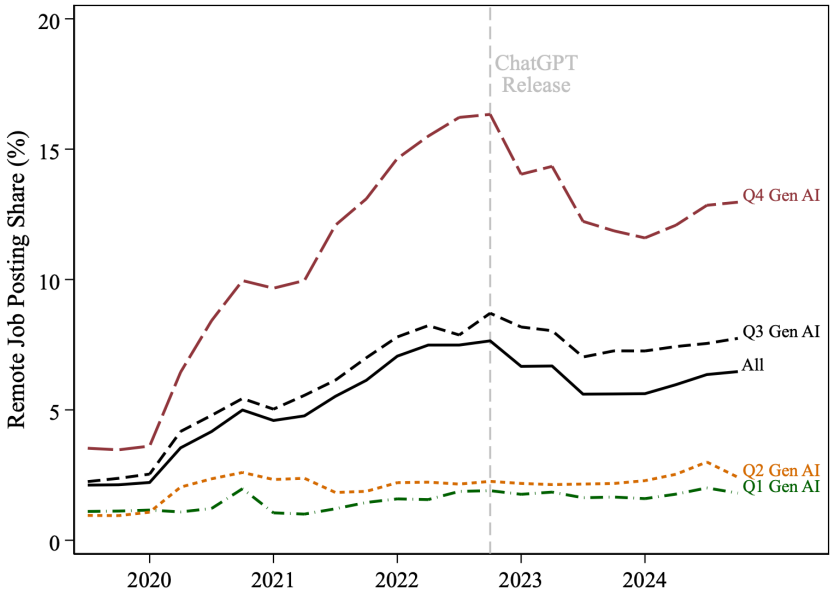
Dependent variable:	Share of Non-Remote Jobs							
Job category:	Gen. AI	High Experience	Medium Experience	Low Experience	College	Advanced degree	Decision making	Communication
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙[Post]× 𝟙[High Gen. AI Exp.]	0.002***	0.017***	-0.011***	-0.004	0.005	0.000	0.016***	0.009**
	(11.90)	(7.07)	(-4.08)	(-1.64)	(1.56)	(0.47)	(4.58)	(2.49)
Observations	220,980	220,980	220,980	220,980	220,980	220,980	220,980	220,980
Estimation:	SDID	SDID	SDID	SDID	SDID	SDID	SDID	SDID
Firm FEs	X	X	X	X	X	X	X	X
Time FEs	X	X	X	X	X	X	X	X

Figure 1:
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.



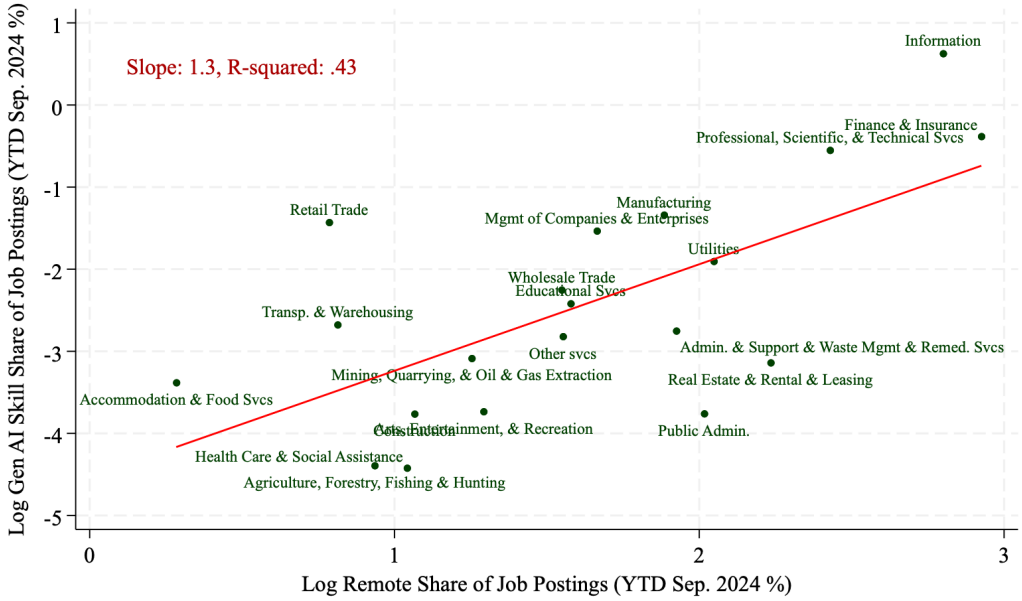
(A) Gen. AI share by remote work quartile



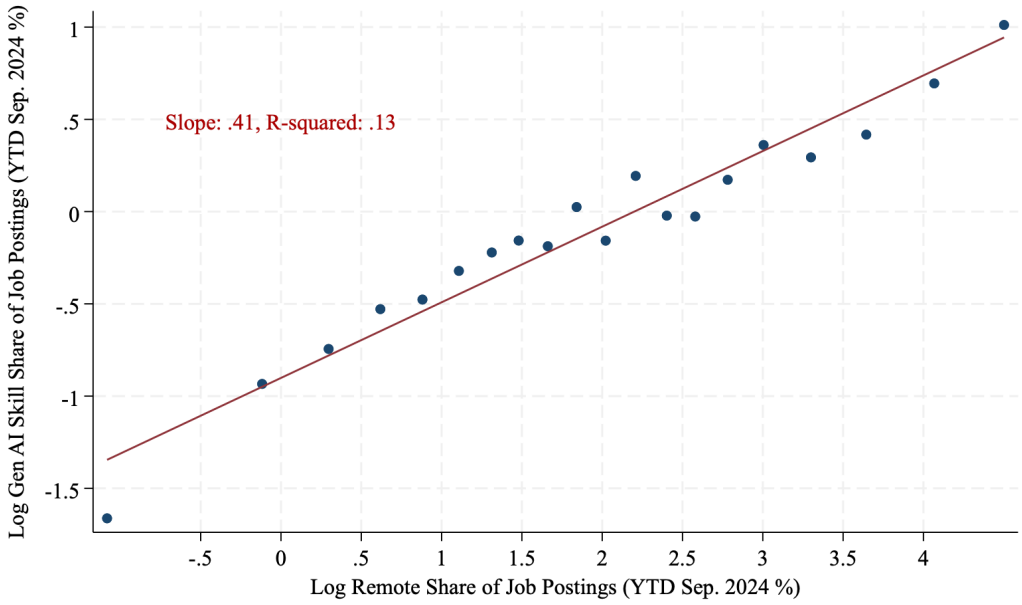
(B) Remote work share by Gen. AI quartile

Figure 2:
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.



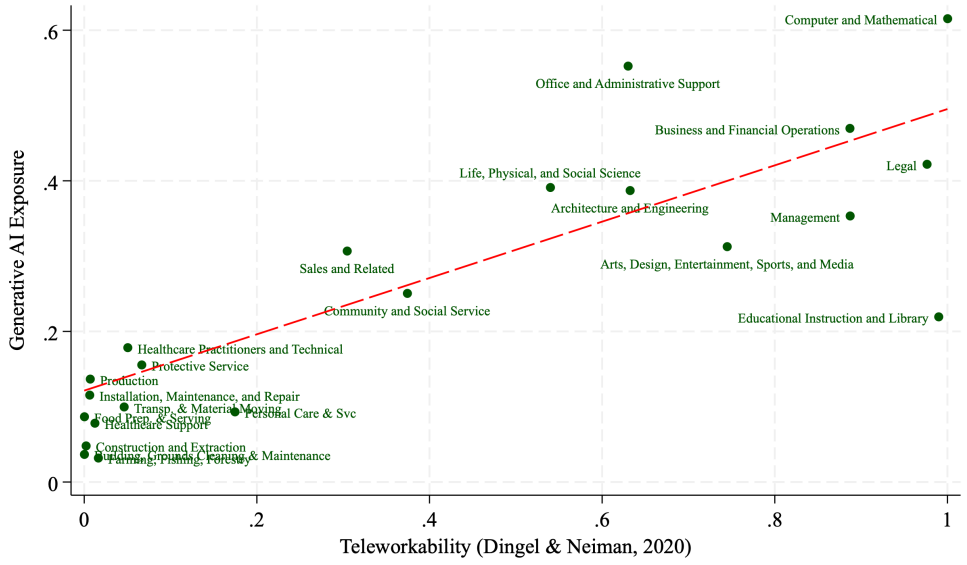
(A) Generative AI and remote work by industry sector



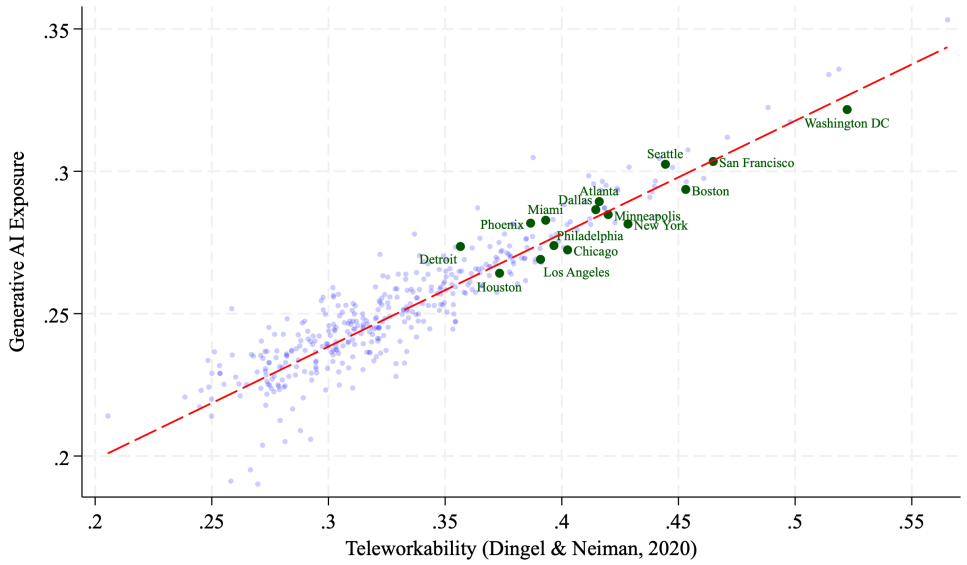
(B) Generative AI and remote work by firm

Figure 3:
Remote Work Suitability and Generative AI Exposure by Occupations and MSA

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 and geographies based on employment weights as of 2022 from the Occupational Employment Statistics. The 15 largest cities by employment are labeled separately in the MSA panel. Lines of best fit in red are estimated with employment weights.



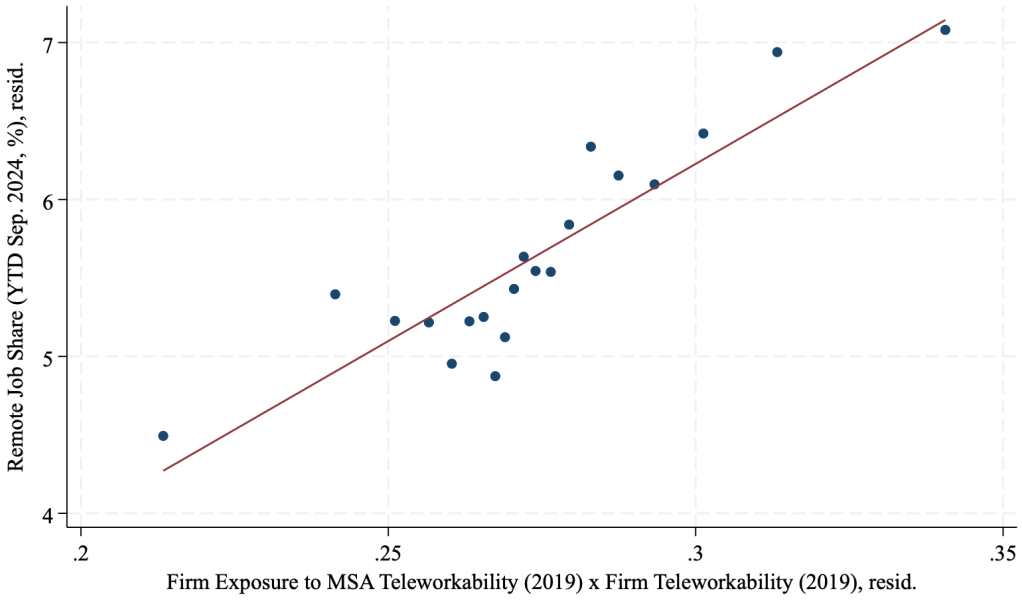
(A) Remote Work Suitability and Gen. AI Exposure by Occupation



(B) Remote Work Suitability and Gen. AI Exposure by MSA

Figure 4:
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 5:
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.

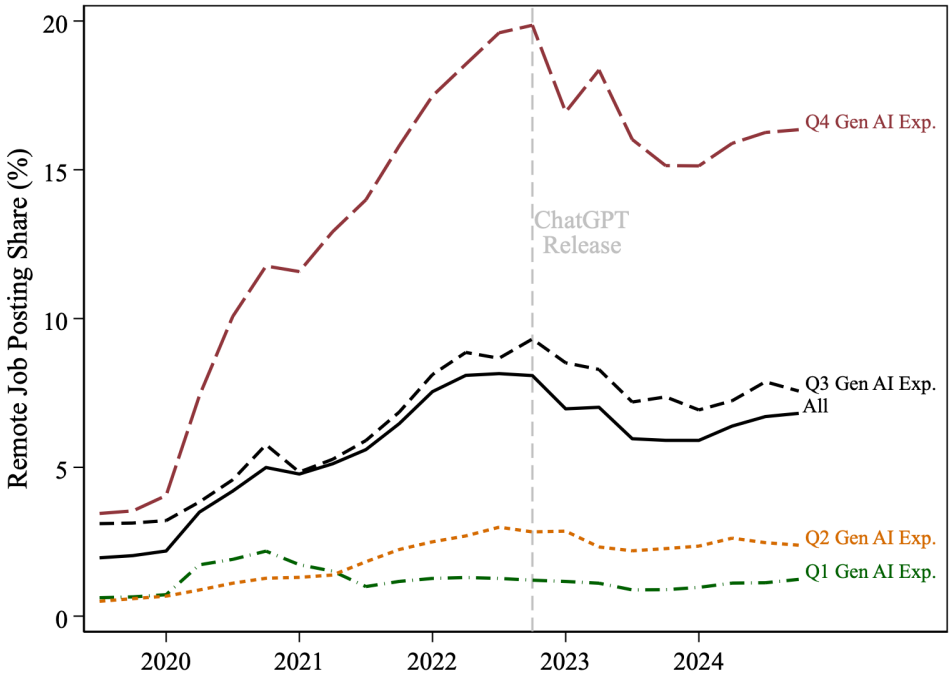
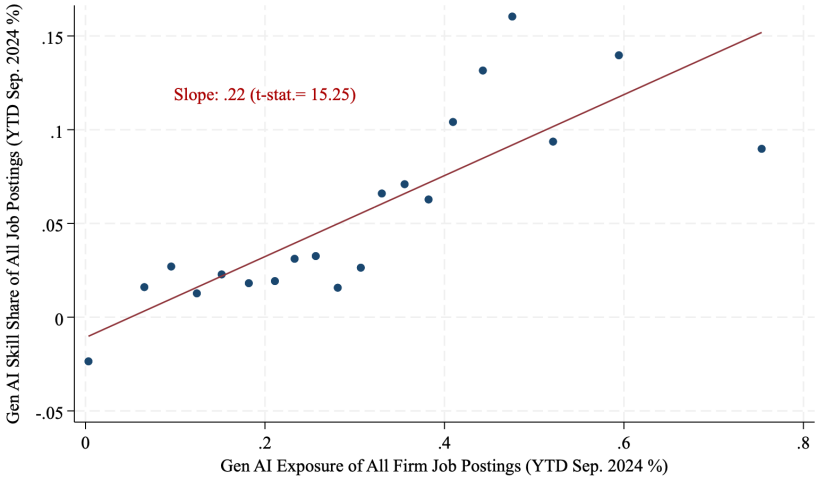
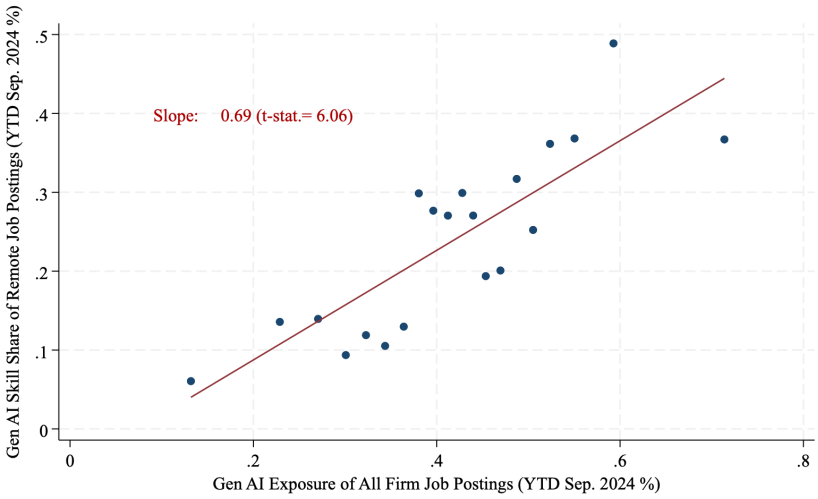


Figure 6:
Generative AI exposure and generative AI adoption by firms

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. The binscatter plots control for NAICS 2-digit sectors fixed effects, and each plot area indicates the corresponding slope and t-statistic for the line of best fit, controlling for the same fixed effects, and clustering standard errors at the firm level.



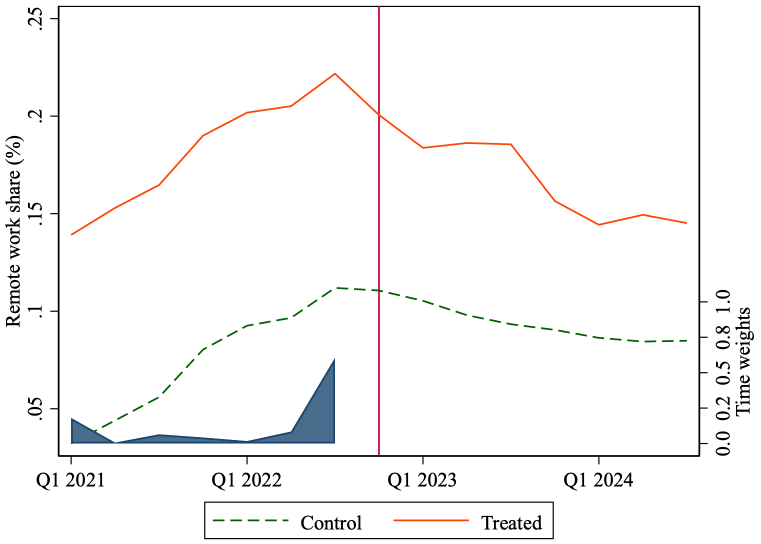
(A) Generative AI exposure and adoption: all jobs



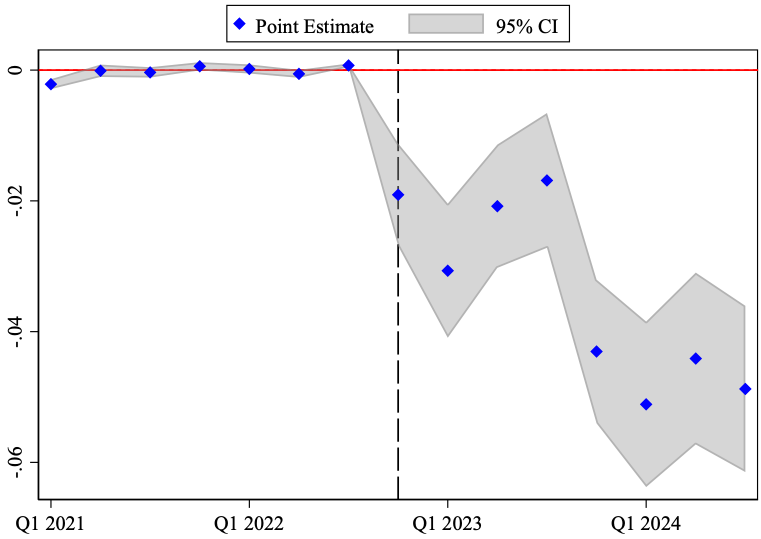
(B) Generative AI exposure and adoption: remote jobs

Figure 7:
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 VII. 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