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Remote Work and Hiring Requirements: Cross-Country Evidence from Job Postings

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Abstract

In this article, we show that remote work is associated with higher skill and qualification requirements in hiring. Drawing on qualitative interviews, we identify several mechanisms through which remote work raises hiring standards. By reducing face-to-face interaction and real-time communication, remote work makes training and employee support more challenging, expands the pool of applicants, and leads employers to rely more on quantifiable metrics. We tested these ideas by analyzing over 50 million job postings from 28 European countries between 2018 and 2021 and found that the shift to remote work is associated with a higher number of required skills and greater work experience for a job. These findings indicate that remote work contributes to skill upgrading in the labor market.

Keywords: remote work, work from home, telework, hiring, skills, qualifications, job requirements, skill upgrading, job postings, labor demand, work experience requirements, on-the-job training, digital work, future of work, cross-country, mixed methods, qualitative interviews

Over the last few decades, labor markets around the world have seen a growing demand for skills and qualifications (Autor et al., 2003, 2006; Berman et al., 1998). This phenomenon, which we refer to as skill upgrading, has been largely attributed to developments in automation technologies, the expansion of international trade, and shifts in labor institutions, all of which have moved labor demand away from middle-skill jobs toward high-skill positions (Acemoglu & Autor, 2011; Goos & Manning, 2007; Goos et al., 2009). In many industries, employers now expect higher levels of education, relevant experience, and specialized skill sets (Cappelli, 2015).

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Changes in task composition—especially those driven by technology—are central to this shift. A large literature shows that automation displaces middle-skill, routine tasks while increasing demand for high-skill labor (e.g., Acemoglu, 2002). Yet, technological advances shape not only what workers do but also where and how they do it. Beyond altering task content, technology transforms how people communicate and interact (Brucks & Levav, 2022). With advances in telecommunications, remote work—also termed distributed work, telecommuting, or working from home—has become far more common (Bloom et al., 2015; Choudhury et al., 2021).

There are reasons to believe that the hiring market for remote work differs from that for in-person jobs. Remote work not only changes how employees communicate and collaborate (Gonsalves, 2020; Rhymer, 2023), but it also expands the labor market by allowing employers to hire from a much broader geographic pool (Aksoy et al., 2022; Hsu & Tambe, 2025). Drawing on theory and detailed qualitative interviews, we identify three processes associated with hiring for remote work that may push employers to set higher skill and qualification requirements.

First, remote work reduces opportunities for face-to-face interaction and real-time communication, making it harder to train and support employees on the job. For example, teaching complex concepts, sharing tacit knowledge, tracking employee learning, and providing close mentoring are all more challenging in a remote setting. These difficulties may lead employers to favor candidates who already have the necessary skills or more advanced expertise. Second, remote work removes geographic constraints, allowing employers to hire from a much larger labor pool (Aksoy et al., 2022; Hsu & Tambe, 2025). Hiring is often limited by location, but remote work allows employers to recruit more broadly. This larger applicant pool enables employers to set higher standards for qualifications and skills. Third, the nature of remote work makes it harder to build trust and monitor employees' effort. As a result, employers may place less emphasis on personality and cultural fit and, instead, prioritize measurable factors, such as skills and credentials, when evaluating candidates. Together, these mechanisms suggest that remote jobs are more likely to require higher skills and qualifications than in-person roles do.

To test this theory, we analyzed a near-universe of online job postings from 28 EU countries between 2018 and 2021. Using a dictionary-based method applied to over 50 million postings, we identified each job's remote work status and hiring requirements.[1] To address potential confounders, we employed two strategies. First, we used extensive fixed effects; our strictest specification includes occupation–employer–country–year fixed effects, comparing jobs with the same occupation, posted by the same employer in the same country and year, differing only in whether the job is remote or in-person. Second, we leveraged the unexpected COVID-19 pandemic, which created variation in social distancing regulations across countries due to geographic and political differences (Aksoy et al., 2022). We used the interaction between these national regulations and an occupation's remote suitability as an instrument for whether a job is remote.

We observed that remote jobs are associated with higher requirements for skills, work experience, and education. Compared to otherwise similar non-

[1] We classify hybrid jobs as in-person and treat remote jobs as fully remote.

remote jobs, remote jobs list about 25 percent more skills, 0.1 additional years of work experience, and 0.04 standard deviations higher educational credentials. Differences in skill requirements account for much of the higher work experience and education requirements; controlling for skills reduces the work experience gap by up to 40 percent. These patterns remain consistent across model specifications, including using national social distancing regulations and an occupation's remote suitability as an instrument, replicating results with the pre-COVID sample, using various fixed effects, and applying alternative measures of skill requirements. We also found higher wages in remote jobs, though these results should be interpreted with caution given the high rate of missing wage information in job postings.

To help illuminate the mechanisms, we examined several moderators. First, the difficulty of providing on-the-job training for remote workers should be more relevant in occupations that require such training. Consistent with this prediction, the difference in skill expectations between remote and in-person jobs is larger for occupations that demand more on-the-job training. Similarly, the skill gap is larger for jobs requiring greater interdependence, suggesting the difficulty of receiving on-the-job support in remote work settings. Second, remote work expands the pool of available candidates, though this effect may be weaker for jobs that are easier to fill and in labor markets with higher slack. Using past job-filling times and local unemployment rates as moderators, we found that differences in skill requirements are smaller when jobs are easier to fill and when unemployment is higher. Third, employers may rely more on quantifiable metrics when filling remote jobs because building trust and culture is more challenging in a remote setting. Consistent with this idea, some models indicate that the skill gap between remote and in-person jobs is slightly larger in lower-trust regions. However, we did not find that remote jobs place greater emphasis on more-measurable skills.

Taken together, these findings suggest that the higher requirements in remote jobs are likely linked to the challenges of on-the-job training and support and to the much larger pool of applicants that employers face when hiring remotely.

To complement our main analyses, we conducted a preregistered supplementary online experiment in March 2024.[2] Participants with hiring experience were presented with a job description and asked to set hiring standards for a position, which was randomly assigned as either remote or in person. Consistent with our job posting analyses, we found that participants specified a greater number of skills and more work experience for remote jobs, though they did not specify higher education credentials.

Our findings make several contributions. First, most research on job upgrading has emphasized the role of automation, globalization, and institutional change. We advance this literature by identifying work arrangements, such as remote work, as a new channel of upgrading and by specifying the mechanisms through which it operates. In particular, we show that remote work is associated with higher hiring requirements, and we highlight mechanisms such as training challenges and larger applicant pools that help to explain this pattern.

[2] Preregistration available at https://aspredicted.org/HTN_78B.

Second, this study broadens the literature on remote work by examining its role in hiring markets. Prior research has focused primarily on employee productivity and performance (Bloom et al., 2015; Choudhury et al., 2021), well-being and work–family outcomes (Gajendran & Harrison, 2007), and communication and collaboration dynamics in distributed teams (Gibson & Gibbs, 2006; Kirkman et al., 2004), with much less attention to recruitment. We show that remote hiring can significantly influence hiring practices.

REMOTE WORK AND HIRING EXPECTATIONS

We define remote work as a work arrangement in which employees perform their tasks outside a traditional office setting (Gibson & Gibbs, 2006). Instead of commuting to a physical workplace, remote workers can work from locations such as their homes or co-working spaces. Remote work differs from in-person work in two key ways. First, employees are physically separated, often by long distances, rather than working side by side. Second, communication is less immediate. Remote work is often asynchronous (Yang et al., 2022), and instead of spontaneous face-to-face interactions, employees rely on tools such as videoconferencing, groupwork software, and email (Bell & Kozlowski, 2002). Time zone differences can further delay communication and reduce opportunities for real-time interaction. These features of remote work may change the skills that employers emphasize when hiring.

To build our theory, we conducted 37 semi-structured interviews, between January and April 2024, with individuals who had substantial experience in remote hiring: 19 hiring managers, 15 executives or senior managers, and 3 mid-level employees. We combined these qualitative insights with existing theories to develop our hypotheses.

We sourced interviewees through Cognism, an employee contact database, and followed a semi-structured protocol. In Online Appendix Section A, we report the full protocol, including the introductory script and core questions. Each interview lasted 30 to 60 minutes. We began by discussing the organization's overall experience with remote hiring. We then explored specific challenges and differences relative to face-to-face hiring.

These interviews helped to shape and refine our emerging theory. Online Appendix Table B.1 lists the interviewees' job titles, tenure, location, and employer characteristics, including size and industry. We next describe the main themes that emerged from these interviews.

Challenges with On-the-Job Training and Support

On-the-job training and support play an important role in shaping employee success (Chen et al., 2013; Ranganathan, 2018; Riley et al., 2017). Most new hires are not equipped with all skills needed to perform a job; hence, both off-the-job and on-the-job training are important. Off-the-job training includes new-hire orientations, various employer-sponsored workshops and classes, and professional certification programs. However, estimates suggest that most employee learning occurs on the job (Becker, 1964; Kahn & Lange, 2014), including through a combination of observation, mentoring and coaching, job shadowing, and hands-on practice (Gibbons & Waldman, 2004; Raffiee & Coff, 2016). Besides training, on-the-job support is also essential to help employees apply what they've learned and overcome challenges they encounter in real-world scenarios. This support can come from mentors, peers, or supervisors who provide feedback, answer questions, and guide employees through challenging tasks. Although sometimes researchers distinguish on-the-job learning from on-the-job support, these are highly related processes, so we combine them in the same discussion.

On-the-job training and support could be significantly more difficult in remote work, largely due to physical separations and the resulting asynchronous communication. Considering past theories and our qualitative evidence, we suggest that such difficulty could manifest in four ways: learning in real time, opportunities for observation, tracking employees' progress, and establishing mentorship.

Learning in real time. The asynchronous nature of remote work makes on-the-job training and support more difficult. On-the-job learning often depends on timely feedback and interaction, which allow employees to correct errors and adjust their approach as tasks unfold (Edmondson, 1999). These real-time interactions enable back-and-forth communication and give learners opportunities to ask questions. In remote settings, such opportunities are more limited: Employees cannot easily turn to nearby colleagues for immediate help. Although telecommunication technologies allow for virtual training and support, these interactions often require more coordination and are less immediate than in-person exchanges. Much on-the-job learning is unplanned and occurs in the moment, making it hard to replicate in remote environments.

In our interviews, respondents often expressed frustration with the inability to get immediate answers when problems arose. One manager explained, "Before [when we were face-to-face], I could just go to my colleagues when I needed help with troubleshooting. Now I have to set up a Zoom call with them, which can require multiple emails. It definitely slows me down" (R36). According to our respondents, these challenges affect both technical and soft skills, ranging from learning how to use specific software to interacting with certain customers. One hiring manager recalled a recent hire who accidentally sent an important, erroneous email to an entire group. Because the new hire was working remotely, they couldn't get immediate help and were slow to perform damage control. Some organizations have attempted to address these challenges by implementing various alternative protocols, but these measures cannot fully replace in-person training and support. For example, one HR manager shared,

> We've attempted to mitigate this [the difficulty of learning remotely] a bit by creating video resources, by creating training guides, but nothing replaces person to person. I can't tell you, over the years, how many times we have updated our training documents. They cover it, but it's a piece of paper. It's not exactly the same as being like, "In this instance, what about this?" You just can't cover everything on paper. (R14)

Tracking employees' learning. A related challenge is the difficulty of tracking and monitoring the learning progress of remote employees. Learning is often an interactive process, requiring instructors to adjust their focus based on student feedback (Goldin et al., 2017). In a remote setting, in which real-time interaction is limited, it can be more challenging for instructors to measure and assess employees' progress. One interviewee explained, ''In [in-person] training, you can tell when you've lost the attention of your audience. In online training, you don't always know if you've lost someone; they're just clicking through the material'' (R31).

The limited ability to track learning progress can create a mismatch between an employer's perception of a remote worker's progress and the worker's own understanding. This disconnect may leave remote workers feeling discouraged, as they may not receive the help and encouragement they need. One HR manager described this dynamic:

> When we were fully remote, trying to assess someone's ability to pick up the skills through independent work and remote training was really challenging. I can think of one person in particular, when we hired her, we thought she was progressing well. She had worked in a similar type of job, just in not as high a volume of an office, and we thought that her learning curve was progressing. She was fully remote the entire time, and she did not feel that she was progressing. She felt overwhelmed, and she felt like she was looking at the things she hadn't learned yet, and was really concerned that she was never going to get up to speed, and decided to leave the position. (R14)

Opportunities for direct observation. Remote work also reduces opportunities for direct observation and the transfer of tacit knowledge (Gilson et al., 2023). In traditional in-person settings, employees can observe experienced colleagues and supervisors performing tasks, thereby gaining insights into processes, techniques, and best practices. Such close observation is challenging in remote work, as employees do not share the same physical space (Mickeler et al., 2023). One respondent noted that, before transitioning to remote work, new hires would shadow experienced employees by sitting next to them—an arrangement that remote work makes impossible.

This lack of physical interaction may limit the transfer of tacit knowledge, such as tips on client management, implicit workplace rules, and detailed technical know-how (Polanyi, 1966; Reagans & McEvily, 2003). Many respondents emphasized that most tacit knowledge is shared during informal in-person interactions, such as hallway conversations, lunch or coffee chats, or after-hours social events (Leonardi, 2014). Without these opportunities, remote employees may struggle to access and learn such knowledge effectively.

Relationships with mentors and colleagues. On-the-job learning and support rely heavily on strong relationships with mentors and colleagues. These relationships establish trust and open communication, which are essential for effective learning and mentoring (Chiaburu & Harrison, 2009; Colbert et al., 2016). Employees who have strong connections with mentors and peers are more likely to feel comfortable asking questions and admitting mistakes, both of which are critical for growth and skill development (Lankau & Scandura, 2002).

Building such relationships may be significantly easier in person than in virtual environments. Physical proximity allows for spontaneous, informal interactions—such as in break rooms, hallways, or social events—that foster camaraderie and trust. These moments help employees connect on a personal level and develop rapport. In remote settings, communication tends to be more structured and scheduled, leaving little room for these casual, relationship-building interactions. Additionally, nonverbal cues, which are important for communication and relationship building, are less visible in virtual environments (Sproull & Kiesler, 1986).

The increased difficulty in building close relationships with mentors and colleagues was evident in our interviews. As one respondent said, ''Without the informal interactions and opportunities for social bonding, it's just hard to build strong connections [in remote work] with the manager and other senior people'' (R19). Another said,

> Being fully remote, especially as an entry-level employee, is really hard. I think you learn in person in your first few jobs how to interact and find mentorship and do all of those intangibles and get to know folks. I can't imagine having just been dropped into a remote world and said, ''Good luck. This is your first professional opportunity.'' (R26)

In another example, an HR professional in the manufacturing industry told the following story:

> We have folks that video on [onboarded virtually] who came into our organization; I was actually talking to him last week. And he said, he was hired for this position, and took this job working with a Linux operating system, which he had never worked with before. Because we are primarily remote workforce, he feels fairly isolated. Because he doesn't feel like he has folks to lean on to help teach them and develop that skill set. (R12)

For all of the above reasons, remote work may significantly increase the challenges of training and supporting employees, which could shift employers' hiring expectations toward candidates who already possess the necessary skills. Employers may also seek workers with more skills when employers know that they cannot provide timely on-the-job support and that workers thus need to deliver tasks and solve problems on their own. Many interviewees shared this sentiment. After describing the difficulty of employees seeking help in real time, one hiring manager suggested that such a challenge in remote training has contributed to higher skill expectations:

> [The difference is] popping over to someone's office or looking over your desk and asking them a few questions versus sending a message to them or trying to get them available on a video call to answer some questions. For things that need to be answered immediately, it would be beneficial if I could just ask right now and then keep working on what I'm working on. But instead, he has to wait for a response from someone, and it's resulted in him feeling like he is solely responsible for things that do not work out, or deadlines that are missed because of his lack of skill set in that area. From our perspective as an employer, it would have been smarter to recruit someone for that position who had established experience instead of putting someone new in that role. (R12)

Another HR professional described the difficulty of building a mentorship and support network in a remote job and suggested that this is a reason to set higher hiring standards:

> Because in a remote setting, because we lack those relationships, it's a lot harder to find an organic mentor within the organization who can help develop the skill sets of

> team members. So when folks are working remotely, we need people that know what they're doing. And if they don't know, they have the experience or internal contacts that they can reach out to . . . But in a remote setting, it's a lot harder to establish that relationship. (R12)

Expanded Applicant Pool

The second feature of remote work is its geographic flexibility (Choudhury et al., 2021). For in-person positions, workers are far more likely to search for and accept jobs near their existing location (Moretti, 2012). Aware of these preferences, many employers place a strong emphasis on the local labor pool. For example, employers often attend career fairs at local universities, create outreach programs targeting nearby communities, and prominently feature their geographic location on online job boards (Holzer et al., 2011).

Remote work removes geographic constraints by allowing employers to search for talent on a much broader scale. With telecommunication technologies, workers can theoretically perform their jobs from almost anywhere in the world. While hiring across countries or regions can present challenges, such as navigating regulations, time zones, and cultural differences, remote work has made this hiring increasingly feasible. As a result, remote positions can lead to a significantly larger pool of candidates (Hsu & Tambe, 2025). Additionally, individuals may be drawn to remote work for its flexibility, reduced commuting time, and ability to create a personalized work environment. Several respondents in our interviews noted that remote work can appear more appealing than in-person jobs, even to those living locally. This preference may further increase the number of applicants for remote jobs.

The size of the applicant pool could significantly influence hiring standards. When the applicant pool is limited, employers may need to relax certain hiring criteria to attract a larger pool of applicants. When the applicant pool is large, employers may impose stricter hiring criteria to screen out candidates (Hershbein & Kahn, 2018; Modestino et al., 2016). For example, requirements for skills, work experience, and college degrees tend to be higher during recessions, when there is a larger number of available workers (Modestino et al., 2020).

In our interviews, nearly all respondents indicated that remote positions attract a significantly larger pool of candidates than in-person positions do. The magnitude of this difference varies, ranging from 20 percent more to 10 or 20 times more. The larger number of applicants for remote positions could allow employers to raise skill requirements. As one recruiter shared,

> The volume [for remote positions] has been overwhelming. We had a pretty steady pipeline from some local avenues. . . . but I post a remote job and I have 600 clicks in two days. I've had to build a hiring process where the barrier to entry is higher, because otherwise the volume is just so completely overwhelming. (R26)

Another HR manager mentioned the need to elevate skill requirements to screen out the ''astronomical'' number of applicants for remote positions:

> The number of applicants we receive for remote positions is astronomical. And it is nearly impossible to actually sort through those in a way that is intentional and meaningful, because [of] the sheer volume that we receive. . . . [Setting higher skill

> requirements] allows us to more easily disqualify candidates based on level of experience and gives us additional tools to help sort through those résumés. (R16)

Although remote positions attract a significantly higher volume of candidates, some research has suggested that these candidates are of lower quality compared to those applying to in-person positions (Emanuel & Harrington, 2024). In our interviews, some respondents suggested that remote candidates are less intentional because they can apply to so many positions, while others indicated that remote candidates are, on average, similar in quality to in-person candidates. Our respondents generally agreed that, regardless of candidates' average quality, the best candidates in remote pools are of higher quality due to the sheer size of the applicant pool. A hiring manager in the design industry compared remote and in-person applicant pools as follows:

> If you're getting 20–30 applicants [for in-person], we are getting about 60–70 applicants [for remote] because you're throwing a wider web. . . . There are some people just applying for positions without reading job descriptions, so I think the quality decreases. But still, we are getting a higher number of applicants. And we may find that diamond in the rough. . . . The quality increases just because of that, because of the higher quantity of people. (R11)

The expanded labor pool means that employers might set higher expectations, but remote work could also lead to an expanded employer pool for workers, resulting in greater competition among employers. Many respondents noted that remote workers may be offered higher wages than in-person workers are. An experienced HR representative in the manufacturing industry said, "I have had less luck with remote workers actually accepting the position. And I think it has a lot to do with the fact that they have a lot more opportunity, a lot more jobs to choose from" (R12). Other respondents pointed out that their organizations' wage setting is based on a set of company guidelines and that they would pay higher wages for remote workers because they are paying more-qualified workers.

As these theories and qualitative findings suggest, the expanded labor pool for remote positions could lead to higher skill expectations and potentially higher wages, suggesting a second mechanism linking remote work and hiring expectations.

A Shift Toward Measurable Qualities

A third theme emerging from our interviews is the growing emphasis on measurable outputs in remote work, which appears to elevate expectations for skills and qualifications. This shift may be driven by two primary challenges: the difficulty of fostering trust and a collaborative culture and the increased reliance on monitoring.

Building trust. The absence of regular face-to-face interactions in remote environments weakens opportunities for building trust and personal connections (Cramton, 2001; Yang et al., 2022). Several respondents underscored the unique challenges of cultivating trust and fostering a collaborative workplace culture in these settings. One HR professional noted,

> It is much harder to make someone feel like they are truly part of the team and culture when everyone is remote. One thing we miss, which I think is a strong aspect of in-person companies, is what I like to call watercooler conversations—those accidental run-ins and opportunities for people to get to know each other on a more personal level. These interactions bring something valuable to the workplace; they add to the culture because you're talking to friends or people you've built relationships with. In a remote workforce, we tend to see more incivility. I think this happens because it's easier to say things online that you wouldn't say face-to-face. Or maybe it's because we're missing body language and social cues that we would have if we were in person. (R12)

Challenges related to trust in remote settings can lead employers to adopt a more transactional view of the employer–employee relationship. If building trust and a collaborative culture is more difficult in remote work, employers may shift their focus to more-measurable aspects of worker quality. Instead of assessing cultural fit and personality, they may prioritize applicants based on their listed skills and qualifications. Several respondents expressed this idea, including one senior executive who stated, ''If I want to build a strong team culture, I'd make sure the work happens in person. But if culture isn't a priority for me, or if I have to hire remote employees, I probably wouldn't focus much on team building. . . . I'd just pay more attention to monitoring their output'' (R2). Another HR manager described a similar attitude:

> I think when you consider the relational aspect, having someone local who can come in, meet the team, and see the office helps them start to picture themselves as part of the organization. There's a sense of camaraderie that comes with that. With remote workers, they know that dynamic isn't there, so the relationship feels a lot more transactional. . . . We don't have to think about cultural fit as much for remote workers. (R12)

Oversight. Beyond the challenges of building trust and culture, the lack of direct oversight in remote work makes performance monitoring more difficult. Managers lose access to informal cues—like body language, overheard conversations, or on-the-spot problem solving—that help them gauge work habits and spot issues. One respondent admitted, ''I miss being able to walk around the floor and check in on employees' progress'' (R19). Because remote supervision is limited, managers often turn to formal performance metrics. This pattern is consistent with principal–agent theory, which suggests that when effort is difficult to observe, evaluators place greater weight on measurable outcomes and observable signals (Jensen & Meckling, 1976; Williamson, 1985). In in-person settings, they could assess dedication by visible signs, such as working late or taking on extra tasks. However, these indicators are hard to observe remotely. As one manager explained, ''If they see you putting in those late hours or working hard on Christmas Day, it creates a perception of dedication. Unfortunately, in a remote environment, those little opportunities to be seen and recognized are lost'' (R18).

Without informal moments of recognition, employers may emphasize more-measurable criteria to ensure accountability, which can result in higher skill requirements. As another manager noted, ''The amount of work we're producing and the way in which we deliver it [in remote work] just feels more stringent. It's much more transactional, and I think the expectation for how much you can deliver in a day is higher'' (R20). The higher expectations for deliverables in remote work could mean that employers demand a broader set of skills and qualifications from job applicants.

Drawing on theories and insights from qualitative interviews, we have proposed several mechanisms—the challenges of on-the-job training and support, an expanded applicant pool, and an emphasis on quantifiable metrics—that suggest higher skill requirements in remote work settings. Next, we test the relationship between remote work and skill requirements and examine these mechanisms.

DATA AND METHOD

To test our propositions, we analyzed over 50 million online job postings from the 28 EU countries between 2018 and 2021. This is the same dataset first used in Zhang and Wang (2024). Job postings provide information on whether a role can be performed remotely and offer detailed insights into employers' hiring expectations, including qualifications and skill requirements. They have been widely used to measure hiring criteria such as education credentials, work experience, and skills (e.g., Deming, 2017; Hershbein & Kahn, 2018). Unlike most large-scale surveys, job postings capture variation across firms and industries and track changes over time. However, there are two key limitations: Job postings may not accurately reflect employers' actual hiring criteria, and not all jobs are advertised online, which could introduce selection bias. These limitations may lead to potential alternative explanations, which we discuss in the Mechanisms section.

We selected a cross-country setting spanning the COVID-19 pandemic to strengthen identification. During this time, countries implemented varying social distancing regulations driven by factors outside the labor market, which we use as an instrument for remote work. In this section, we introduce the dataset and describe the sample characteristics, followed by the construction of key variables and an outline of our analytical strategy. To save space, we include only essential information in the main manuscript and provide additional details in the online appendices. We also conducted an online experiment, which is presented as a stand-alone study in a separate section following the main results.

Cross-Country Job Posting Data

Our primary data source includes approximately 50 million job postings from the 28 EU countries between 2018 and 2021, spanning nearly all industries and occupations. The dataset is provided by Lightcast (formerly Burning Glass Technologies), an employment analytics and labor market information company. In collaboration with the European Centre for the Development of Vocational Training (Cedefop), Lightcast systematically scraped and parsed data from around 300 selected job portals daily, covering more than 60,000 websites across the 28 countries. These portals include private job sites, public employment services, recruitment agencies, online newspapers, and corporate job boards.

Lightcast focused on the major job portals in each sampled country, with each portal containing links to several thousand websites. Online Appendix Table D.1 details the number of postings per country, and Appendix Table D.2

provides examples of targeted portals for each country. Larger labor markets, such as Germany, include over 100 portals and more than 10 million postings. Even smaller labor markets, like Malta, are represented with two major job portals and 18,147 postings. This extensive coverage ensures that our sample represents a substantial share of job openings across the labor markets.

To assess the representativeness of our sample, we compared our job posting data with official job vacancy statistics from EU countries (see Online Appendix Section D). Overall, our job postings capture approximately 60 percent of job vacancies across the 28 EU countries.[3] When comparing the job posting sample with official statistics across geography, occupation, industry, and time, we found a slight over-representation in professional and managerial occupations, service and technology industries, more-developed economies, and recent periods. However, across other dimensions, the job posting data align closely with official vacancy statistics (see Online Appendix Section D for further details). These coverage patterns are similar to those reported for U.S. job posting data.

Identifying Remote Work

To identify remote jobs, we developed a comprehensive dictionary and applied it to job postings. First, we randomly selected 2,000 job postings from the English-speaking countries in our sample and asked research associates to manually identify key phrases associated with remote work. To avoid ambiguity, they focused on phrases rather than individual words. For example, the word "remote" could refer to "remote training" or "remote interview" rather than "remote work." We selected phrases that reliably indicate remote work, such as "work from home," "work remotely," and "remote position." Additionally, the associates identified phrases that explicitly indicate the absence of remote work, such as "work remotely: no," to help identify and filter out false positives. We focused on only fully remote positions and did not consider hybrid positions as remote.

Second, after compiling the dictionary of key phrases related to remote work, we validated each phrase by examining its occurrences in our full sample of job postings. For each phrase, we randomly selected ten postings containing that phrase and manually reviewed them to determine whether the job was indeed remote. To be included in the dictionary, a phrase needed to achieve a 90 percent accuracy rate. During this process, we excluded postings containing false positive phrases, such as "no remote work is allowed," to avoid skewing the validation results.

Third, we manually validated the accuracy of our dictionary-based method and compared it to alternative methods using OpenAI's GPT models. To do this, we randomly selected 1,000 English-language job postings and asked two research associates to independently review each posting and identify whether it allowed remote work. For the few instances when the associates disagreed, we discussed each one collaboratively to reach a consensus. Ultimately, we identified 62 positions as remote and the remaining 938 as non-remote.

[3] Estimated using Eurostat Job Vacancy Statistics. Coverage is comparable to U.S. datasets based on Lightcast, which typically range from 40–80 percent.

We then tested the accuracy of our dictionary-based method on 1,000 job postings and compared it to OpenAI's GPT-4 model. Our dictionary-based method identified 60 remote positions, correctly classifying 57 with three false positives, and missed five remote positions. In comparison, GPT-4 also identified 60 remote positions but correctly classified 55, with five false positives, and missed seven remote positions. Overall, our dictionary-based method achieved 99.2 percent accuracy in identifying the remote status of jobs.

Finally, we translated our dictionary of key phrases for remote work and false positives into 23 languages: Bulgarian, Croatian, Czech, Danish, Dutch, Estonian, Finnish, French, German, Greek, Hungarian, Italian, Latvian, Lithuanian, Maltese, Polish, Portuguese, Romanian, Slovak, Slovenian, Spanish, Swedish, and Turkish. These languages are official in at least one country in our sample. We used GPT-3.5 for the translations and ensured that the phrases reflected common terms used in each local labor market. Details on the translation process and the full list of phrases are provided in Online Appendix Section E.

Using this dictionary-based method, we identified 5 percent of job postings as remote, with 2 percent classified as remote prior to the COVID outbreak and 8 percent after. The distribution of remote work will be discussed in greater detail in the Results section.

Identifying Skill Requirements

Job postings often reveal the skills that employers expect from candidates, typically highlighted in sections describing job duties and required qualifications (see Online Appendix Figure F.1 for examples). The Lightcast dataset uses standardized ESCO level 3 skills.[4] ESCO is a multilingual classification system that identifies and categorizes skills and occupations relevant to the EU labor market (European Commission, 2021). It defines 13,890 skills, ranging from general ones like *work in teams* to highly specific ones such as *ICT system programming* and *JavaScript*. The Lightcast team uses these skills as the comprehensive universe of skill requirements. Details of Lightcast's skill-coding process and our validation methods are provided in Online Appendix Section F.

The Lightcast team identifies all ESCO skills listed in each job posting. On average, job postings list seven required skills, with 17 percent including none and 47 percent specifying more than 10. To validate Lightcast's skill coding, we aggregated the skill requirements at the occupation level and compared them with ratings from the U.S. Bureau of Labor Statistics' Occupational Information Network (O*NET). The results show moderate correlations across skill categories, ranging from 0.3 to 0.5, demonstrating a relatively strong alignment between Lightcast's coding and O*NET ratings. Additional details can be found in Online Appendix Figure F.2. In addition to detailed skill requirements, the Lightcast team extracts information on each job posting's education and work experience requirements, standardized EU industry codes (NACE level 2), occupation codes (ESCO level 4), and geographic locations (Nomenclature of Units for Territorial Statistics [NUTS] level 2).

[4] ESCO stands for European Skills, Competences, Qualifications, and Occupations.

Dependent Variables: Skill and Qualification Requirements

We used three dependent variables to measure employers' demand for skills and qualifications. The first is the number of unique skills listed in a job posting, which is the count of ESCO skills identified by Lightcast's research team. Since this variable is right-skewed, we added one and applied a log transformation.

Our second dependent variable is the years of work experience required. Lightcast's research team coded this using an eight-level categorical scheme: no experience, up to 1 year, 1–2 years, 2–4 years, 4–6 years, 6–8 years, 8–10 years, and over 10 years. We recoded this into a numerical variable, assigning 0 for no experience, 1 for up to 1 year, 1.5 for 1–2 years, 3 for 2–4 years, 5 for 4–6 years, 7 for 6–8 years, 9 for 8–10 years, and 10 for over 10 years. We treated job postings without explicit experience requirements as not requiring experience and assigned them a value of 0. This approach assumes that omitting experience requirements suggests they may not be critical for the role. Notably, the number of skills required and years of work experience required are positively correlated ($r = 0.15$), reflecting the expectation that candidates with more experience are likely to possess more skills.

The third dependent variable is the education credentials listed in a job posting. Lightcast coded education requirements on an eight-point scale: primary education, lower secondary education, upper secondary education, post-secondary non-tertiary education, short-cycle tertiary education, bachelor's degree or equivalent, master's degree or equivalent, and doctoral degree or equivalent. We used this eight-point scale as our measure of education credentials, as it aligns with the widely used International Standard Classification of Education developed by UNESCO to enable cross-country comparisons of educational statistics. In our sample, 15 percent of jobs require at least a bachelor's degree (tertiary level or higher). Summary statistics for the three dependent variables—number of skills required, years of required work experience, and education credentials—are provided in Online Appendix Section G.

Fixed Effects Models

Our baseline models directly compare hiring requirements of remote and non-remote jobs. To ensure a fair comparison of otherwise similar jobs, we included fixed effects for occupation–country, job portal, and the year the job was posted. In the main manuscript, we use ESCO level 4 for occupation, while Online Appendix Table I.1 applies the more detailed job title level in the fixed effects.

To account for firm-level differences that may influence both remote work conditions and skill expectations, we included firm fixed effects. Our strictest model incorporates occupation–firm–country–year fixed effects, as well as a separate fixed effect for the job portal. This approach enables us to compare otherwise identical jobs, differing only in whether they allow remote work. Our strictest baseline model can be written as follows:

$$Skill_{jtfcy} = p_1 \cdot Remote_{jtfcy} + p_2 \cdot X_{jtfcy} + FE_{tfcy} + FE_p + u_{jtfcy}, \qquad (1)$$

where $Skill_{jtfcy}$ are the three hiring requirements—the number of skills, education credentials, and work experience—for job posting j, with the occupation t, posted by firm f in country c at time y. $Remote_{jtfcy}$ is a binary variable indicating whether a job is remote. X_{jtfcy} are job-level controls, including the number of skills listed. FE_{tfcy} is fixed effects on occupation–firm–country–year, FE_p is fixed effects for job portal p. For robustness checks, we included fixed effects for job titles and tasks listed in job postings. All models are estimated using ordinary least squares (OLS).

To predict requirements for education credentials and work experience, we ran models both with and without the number of skills as a control variable. This approach allowed us to assess how much of the increased expectations for work experience and education credentials are driven by the demand for more skills.

An Instrumental Variable Approach

To strengthen identification, we used an instrumental variable (IV) approach that exploits the COVID-19 pandemic as a natural experiment. We instrumented remote work, using the interaction between occupation-level teleworkability and country-level social distancing regulations. In this shift-share design, teleworkability captures an occupation's pre-pandemic suitability for remote work, while social distancing regulations provide the time- and country-level shock. For example, health care workers require physical presence and are less teleworkable, whereas software developers can more easily work remotely. Countries also varied in policy responses, with some implementing strict lockdowns and others adopting more-relaxed measures.

The validity of the instrument rests on two assumptions. First, teleworkability must be stable over time. Because it is based on pre-pandemic data, it reflects underlying job tasks that are unlikely to change quickly, although some adaptation may have occurred during the pandemic. Second, social distancing regulations must affect hiring only through remote work. To address this concern, we included occupation–country–year fixed effects, which absorb time-varying country-level shocks such as macroeconomic conditions and policy changes.

We measured social distancing using the Oxford Government Response Tracker (OxCGRT) stringency index (Hale et al., 2021), which ranges from 0 to 100 and captures lockdown intensity. The index varies across countries and over time, and it is set to zero before COVID-19. Teleworkability is measured using the index from Sostero and colleagues (2020), based on pre-pandemic survey data, which assigns each occupation a score between 0 (non-teleworkable) and 1 (fully teleworkable).

MAIN RESULTS

Results indicate that remote work significantly increases skill and qualification requirements in hiring. In OLS models with strict fixed effects, remote work is associated with requiring more skills, additional years of work experience, and higher education credentials. Similarly, IV estimates confirm that remote work raises requirements for both the number of skills and work experience.

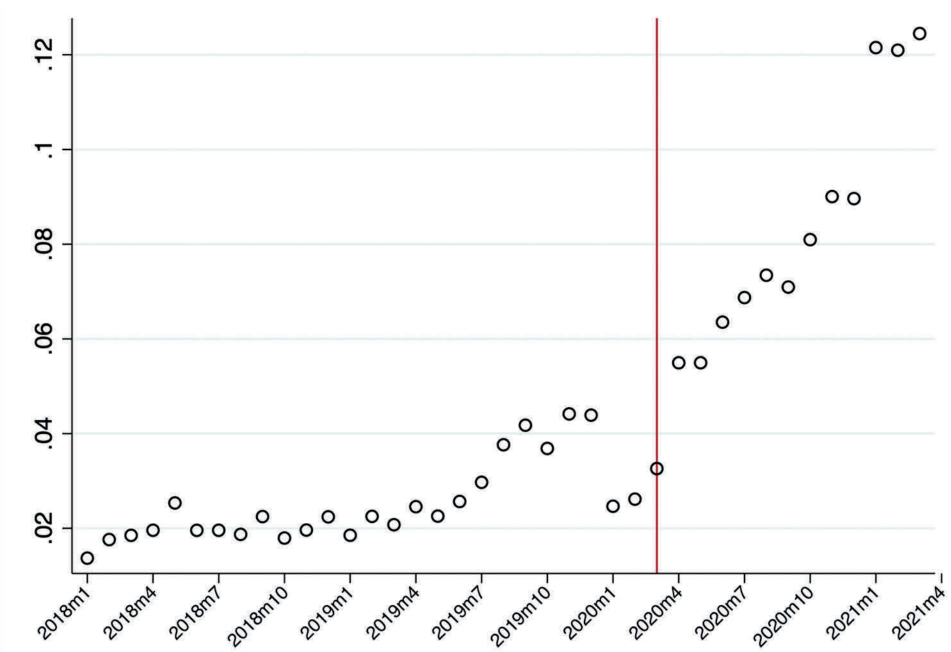
This section begins with an overview of the distribution of remote work across 28 EU countries from 2018 to 2021. We then examine the relationship between remote work and hiring requirements, using both OLS and IV models. We also present several additional analyses that we conducted, including examining wages as an outcome, comparing hybrid and in-person work, and using firm characteristics as moderators. Next, we present evidence on potential mechanisms driving these results. Finally, we explain how we carried out an online experiment to confirm our main findings.

Distribution of Remote Work

Figure 1 displays the monthly proportion of remote jobs from January 2018 to March 2021. Before the sudden outbreak of COVID-19 in March 2020, the proportion of remote jobs ranged from 2 to 4 percent. However, even during this pre-pandemic period, remote work was steadily increasing, rising from 0.8 percent in January 2018 to 3 percent by February 2020, reflecting a growing trend in the global labor market. The onset of the pandemic significantly accelerated this trend. Starting in March 2020, the proportion of remote jobs increased rapidly, surpassing 12 percent by March 2021. Since our data end in March 2021, we are unable to observe how remote work has evolved following the pandemic.

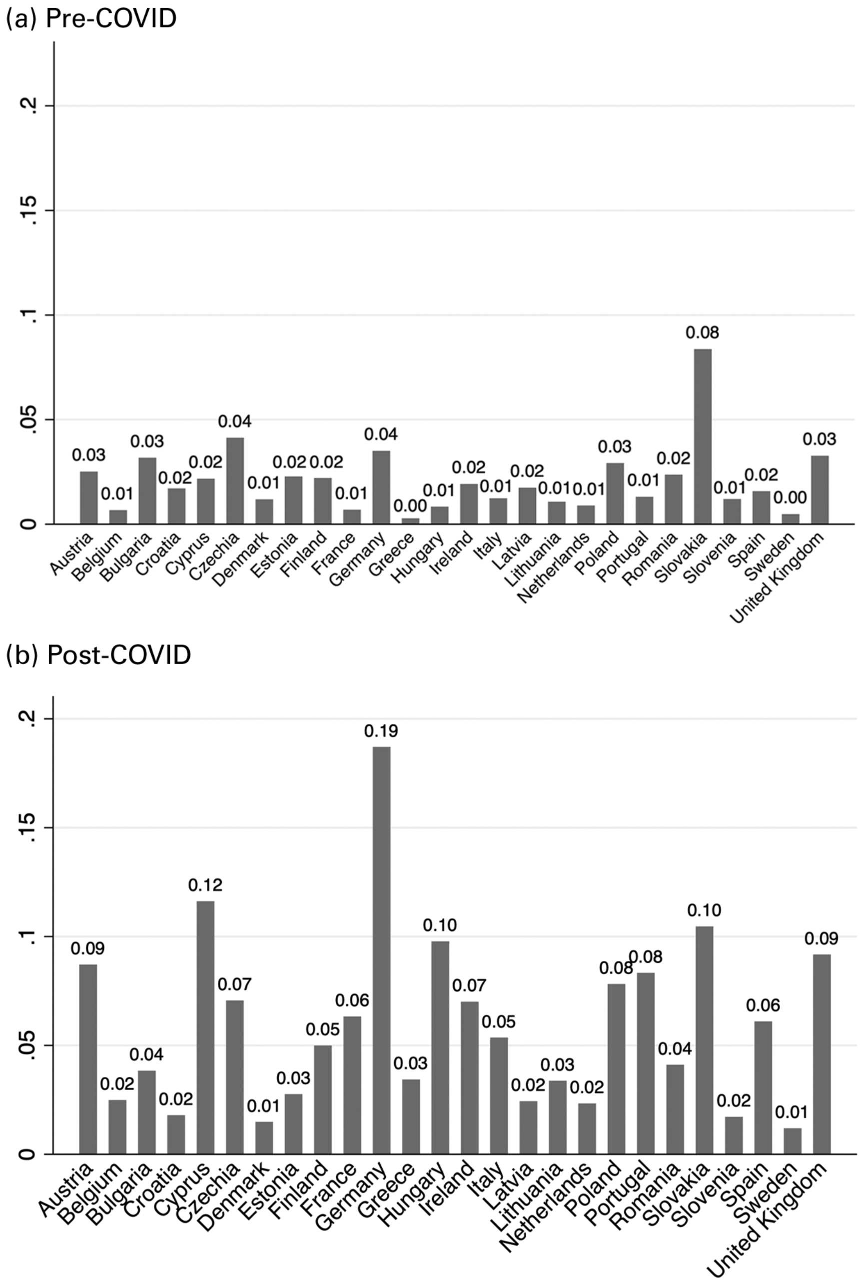
Figure 2 presents the proportion of remote jobs by country, comparing pre- and post-COVID periods. While nearly all countries experienced an increase in remote jobs after the pandemic began, the size of this increase varied significantly. Central European countries, including Austria, Bulgaria, Germany, and Poland, saw the largest jumps. For example, in Germany, the proportion of remote jobs rose from 4 percent before COVID to 19 percent afterward. In contrast, Northern European countries, such as Denmark, the Netherlands, and

Figure 1. Proportion of Jobs Being Remote: Sorted by Month•



• The vertical line signals the onset of the COVID pandemic in 2020.

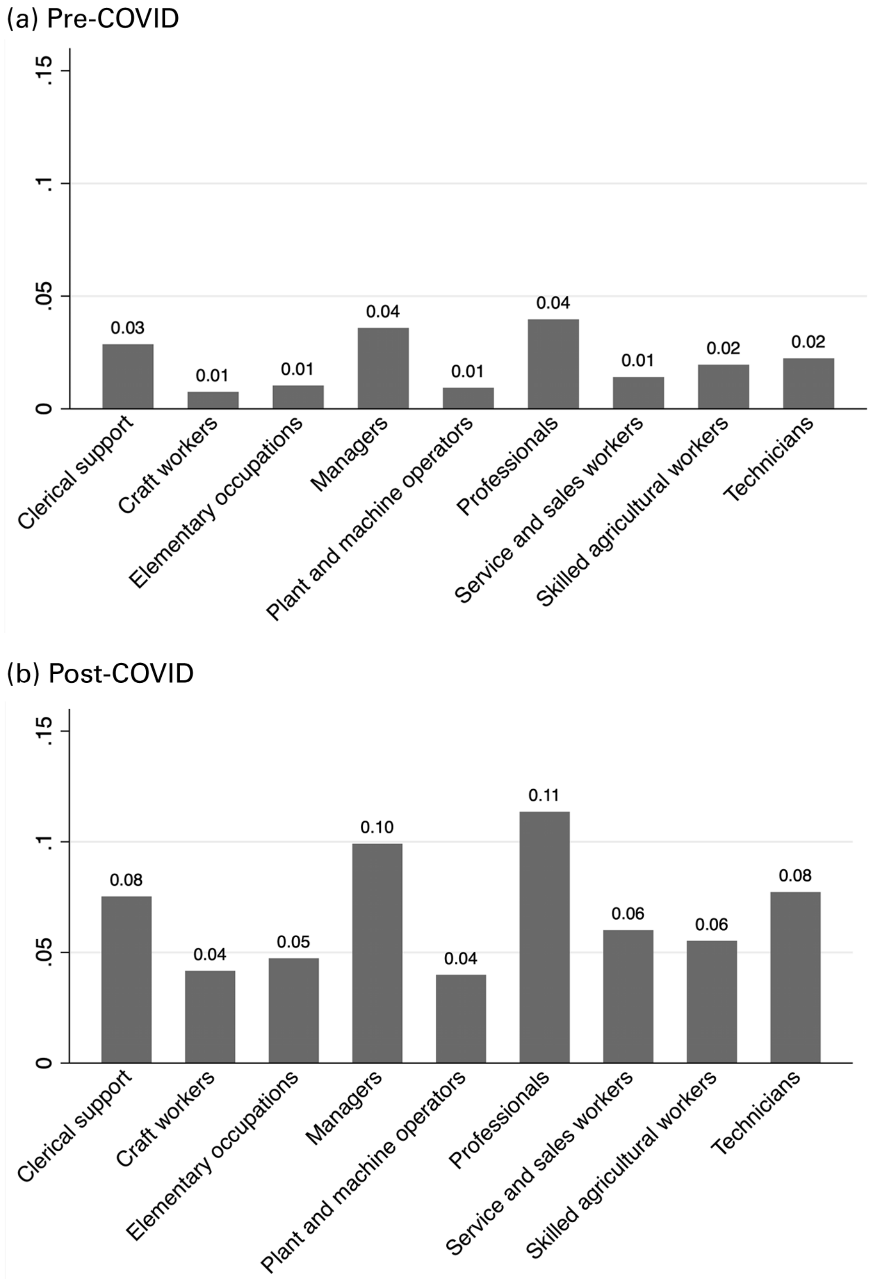
Figure 2. Proportion of Jobs Being Remote: Sorted by Country



Sweden, experienced only moderate increases. For instance, Sweden's share of remote jobs rose from 0 percent pre-COVID to just 1 percent post-COVID. These differences likely reflect variations in countries' infection rates and their strategies to address the pandemic.

Figure 3 shows the proportion of remote jobs by broad occupational categories, separately for pre- and post-COVID periods. White-collar occupations,

Figure 3. Proportion of Jobs Being Remote: Sorted by Occupation



such as managers, professionals, and clerical support workers, had the highest proportion of remote work before the pandemic and saw the largest increases afterward. For example, the share of remote jobs rose from 4 percent to 10 percent for managers and from 4 percent to 11 percent for professionals.

These patterns align with the expectation that remote work is more feasible for office-based roles compared to jobs in services or manufacturing.

Descriptive Patterns

We now examine how employers' hiring expectations have changed over time. Figure 4 provides a descriptive comparison of remote and in-person jobs. Remote jobs, on average, list higher requirements than non-remote jobs do for the logged number of skills (3 vs. 2.5), work experience (2.1 vs. 1.8), and education credentials (4.6 vs. 4.5). These patterns align with our propositions. However, given potential differences between occupations and firms, below we use OLS models with strict fixed effects to control for confounders related to occupation, firm, and country.

OLS Estimates

Table 1 compares the hiring requirements of remote and in-person jobs. From left to right, the table uses three dependent variables: the number of skills (log), years of work experience, and education level. For each dependent variable, two model specifications are presented: one with occupation–country–year fixed effects and another with occupation–country–employer–year and job portal fixed effects.

Models 1 and 2 show that remote work is associated with a 25 to 42 percent increase in the number of required skills, respectively. In Models 3 and 4,

Figure 4. Descriptive Differences Between Remote and In-Person Positions

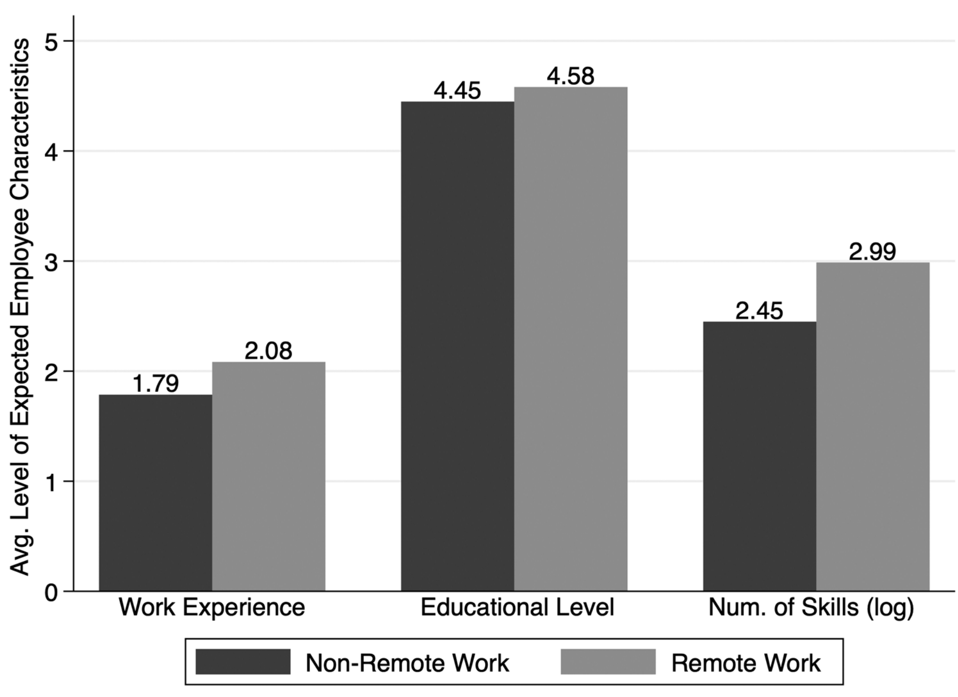


Table 1. Linear Estimation of Hiring Requirements•

	Number of Skills (log)		Work Experience				Educational Level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote work	0.351***	0.222***	0.195***	0.117***	0.119***	0.0774***	0.0823***	0.0615**	0.0648***	0.0492*
	(0.00806)	(0.00934)	(0.0115)	(0.0138)	(0.0109)	(0.0123)	(0.0187)	(0.0197)	(0.0180)	(0.0193)
Number of skills (log)					0.217***	0.180***			0.0497***	0.0555***
					(0.00594)	(0.00825)			(0.00402)	(0.00384)
Observations	51751672	41372416	51751672	41372416	51751672	41372416	51326238	41012325	51326238	41012325
R^2	0.594	0.778	0.062	0.368	0.066	0.369	0.324	0.577	0.325	0.578
Fixed effects:										
Occupation × Country × Year	Yes		Yes		Yes		Yes		Yes	
Occupation × Employer × Country × Year		Yes		Yes		Yes		Yes		Yes
Job portal		Yes		Yes		Yes		Yes		Yes

*$p < .05$; ** $p < .01$; *** $p < .001$

•Standard errors are in parentheses. All models are clustered at the firm level.

remote work is also associated with an increase of 0.1 to 0.2 years in work experience requirements. This difference is substantial, considering the mean required experience is 1.7 years, with a median of one year. Models 7 and 8 reveal that remote work raises education requirements by 0.06 to 0.08, equivalent to 0.04 to 0.06 standard deviations. The inclusion of stricter fixed effects for employers and job portals in Models 2, 4, and 8 reduces the effect size of remote work, suggesting that part of the differences may be driven by variations across employers.

Our proposition suggests that the higher hiring requirements for education credentials and work experience in remote jobs are primarily driven by greater skill demands. To test this, Models 5–6 and Models 9–10 include the number of required skills as a control variable and examine how its inclusion affects the relationship between remote work and work experience or education level. Controlling for skills reduces the association between remote work and work experience by 34–39 percent (Models 5–6) and the association between remote work and education level by about 20–21 percent (Models 9–10). These findings indicate that the elevated requirements for education and experience in remote positions are largely explained by employers' heightened skill expectations.

Thus, when comparing the same jobs posted by the same firm within the same country, we found distinct hiring requirements for remote and in-person positions. Consistent with our hypothesis, employers hiring for remote jobs expect candidates to possess more skills, which, in turn, drives higher expectations for work experience and education credentials.

IV Estimates

We next present analyses using an instrumental variable (IV) approach to address concerns that remote work is not randomly assigned. We instrumented remote work status, using the interaction between a country's social distancing policies during the COVID-19 pandemic and an occupation's suitability for remote work. To further mitigate concerns about unobserved heterogeneity, we included occupation–country–year fixed effects, which effectively control for each country's time-varying economic conditions and occupation-specific shocks within a given year. Additionally, we included fixed effects for occupation–employer–country–year to ensure that we compared similar jobs within the same company under comparable labor market conditions.

Table 2 reports the instrumental variable estimate of the effect of remote work assignment on hiring expectations. We present two model specifications: the first with occupation–country–year fixed effects and the second with job portal and occupation–country–employer–year fixed effects. In Models 1–2, we show the first-stage results that predict a job's remote work assignment, using the interaction term between a country's social distancing stringency index and an occupation's teleworkability index. We found that, consistent with our expectations, a one standard-deviation increase in the interaction term increases remote work assignment by 1.94 percent, with a highly significant F-statistic of 260.6.

We present the second-stage results in Models 3–8. Consistent with our OLS estimates, remote work increases the number of skills and years of work experience. In the strictest models (Models 4 and 6), a 10 percentage point

Table 2. Instrumental Variable Estimation of Hiring Requirements•

	First Stage: Remote Work		Number of Skills (log)		Work Experience (in Years)		Educational Level	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Remote work			2.357***	5.657***	0.549***	2.046***	–1.021***	–0.123
			(0.0899)	(0.176)	(0.142)	(0.164)	(0.0770)	(0.118)
Social distancing index × Teleworkability index	0.00107***	0.000745***						
	(0.0000295)	(0.0000207)						
Observations	50538308	40321201	50538308	40321201	50538308	40321201	50114030	39962185
R^2	0.092	0.533	–0.274	–1.905	–0.001	–0.017	–0.038	–0.001
Fixed effects:								
Occupation × Country × Year	Yes		Yes		Yes		Yes	
Occupation × Employer × Country × Year		Yes		Yes		Yes		Yes
Job portal		Yes		Yes		Yes		Yes

$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

•Standard errors are in parentheses. All models are clustered at the firm level.

increase in remote work assignment increases the number of required skills by 76 percent and requires 0.2 additional years of prior work experience, compared with in-person jobs that are otherwise similar in occupation, location, employer, and year.

At the same time, IV estimates do not find a significant positive association between remote work and requirements for education credentials. This result likely reflects omitted variable bias in our OLS estimates: Firms posting remote jobs may systematically differ in their reliance on education as a screening credential in ways not fully absorbed by our fixed effects. However, we cannot rule out that social distancing regulations affected the educational composition of the labor supply—for example, by disproportionately pushing higher-educated workers into the remote labor market—which could independently influence educational hiring standards through channels other than remote work adoption.

The IV estimates are larger than the corresponding OLS estimates, which may reflect downward bias in OLS due to selection into remote work: Firms that voluntarily adopt remote work are likely better equipped to manage remote coordination and training and, therefore, may not substantially adjust their hiring requirements. It could also reflect that the IV identifies a local average treatment effect for jobs pushed into remote work by social distancing regulations—jobs that would not have gone remote otherwise—and these may be precisely the cases in which employers had to adjust their hiring criteria most dramatically.

Different Types of Skills

We divided skills into four broad categories: cognitive skills, social interaction with coworkers, social interaction with customers, and information and communication technology (ICT) skills. Table 3 shows that remote work is associated with higher skill expectations across all four categories. When we included the total number of skills as a control variable to examine relative differences, we found that remote work predicts higher requirements in ICT, cognitive, and customer service skills, while showing inconsistent effects for social interaction with coworkers. Social skills may be less emphasized in remote positions due to fewer opportunities for face-to-face interactions. In contrast, ICT and customer service skills are often developed through hands-on experience, and the lack of on-the-job training or support in remote settings may lead employers to expect candidates to possess these skills up front. Additionally, remote work settings require workers to operate with minimal in-person guidance, making strong cognitive abilities essential for effective self-direction.

Do Firm Characteristics Matter?

We examined whether the effect of remote work on hiring expectations varies across firms, particularly considering their remote capabilities. Firms with more experience and established systems for remote work may exhibit smaller differences in hiring requirements between remote and non-remote positions. Greater remote capabilities could also enhance training effectiveness, further reducing these disparities. While we lacked a direct measure of remote capability, we used the proportion of remote jobs within each firm before COVID-19

Table 3. Linear Estimation of Hiring Skill Requirements: Separated by Skill Categories•

	Cognitive Skills		Social Interaction with Coworkers		Social Interaction with Customers		Technical Skills	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Remote work	0.182***	0.0408***	0.101***	–0.0357***	0.254***	0.168***	0.305***	0.122***
	(0.00904)	(0.00507)	(0.0127)	(0.00807)	(0.00724)	(0.00501)	(0.0211)	(0.0169)
Number of skills (log)		0.729***		0.707***		0.442***		0.944***
		(0.0129)		(0.0145)		(0.00614)		(0.0261)
Observations	36419125	36419125	36419125	36419125	36419125	36419125	36419125	36419125
R^2	0.617	0.696	0.683	0.740	0.733	0.759	0.728	0.756
Fixed effects:								
Occupation × Employer × Country × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job portal	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

•Standard errors are in parentheses. All models are clustered at the firm level.

as a proxy, assuming that firms with a higher proportion of remote positions have more experience and infrastructure to support remote work. Online Appendix Table L.3 presents this proportion as a moderator. However, our results do not show a consistent pattern in how a firm's remote adoption influences hiring expectations. Additionally, remote work may be easier to implement in larger firms that can better adapt to remote conditions, but Online Appendix Table L.3 does not provide strong evidence supporting this hypothesis.

Hybrid Versus Fully Remote

Our analyses focus on fully remote work, but many jobs now adopt a hybrid approach in which employees work from the office a few days a week. Most forms of hybrid work are not fundamentally different from in-person work. In typical hybrid arrangements, employees spend some time in the office, enabling face-to-face interactions and on-the-job skill development. Additionally, hybrid work does not significantly expand the labor pool to far-away locations in the same way that fully remote work does. For many of the mechanisms we examined, hybrid work likely functions more like in-person jobs than fully remote ones.

To address this, we incorporated analyses of hybrid work. In our sample, only 0.014 percent of jobs are classified as hybrid, reflecting that hybrid work had not yet become a standard posting category during our 2018–2021 sample period. Their skill requirements closely resemble those of in-person roles (see Online Appendix Table I.5), consistent with our argument that hybrid work functions more like in-person than fully remote work, though these results should be interpreted with caution given the small sample size.

Wage Differences

Our final analyses in this section explore wage differences between remote and in-person jobs. Since it is uncommon in many European countries to include wage information in job postings, we have wage data for only 20 percent of the jobs in our sample. This limited representation raises concerns about potential selection bias, as the decision to disclose wage information may be endogenous and influenced by unobserved factors that also affect remote work. Therefore, we present this analysis as suggestive rather than conclusive findings.

Lightcast's research team standardizes all wage information to an hourly basis and categorizes it into 13 buckets, ranging from under 6 Euros per hour to over 90 Euros per hour. Table 4 presents OLS models predicting a job's wage, measured using Lightcast's 13-point scale. In Model 1, which includes occupation–country–year fixed effects, we did not find a statistically significant association between remote work and wage. However, in Model 2, which applies stricter occupation–country–employer–year fixed effects, we found that remote jobs are associated with higher wages—0.06 standard deviations above in-person jobs. This suggests that the same employer would offer higher wages for a remote job compared to an in-person job with the same title, posted in the same year.

Table 4. Linear Estimation of Job Posting Salary•

	OLS				IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Remote work	0.0542	0.204***	0.0157	0.197***	1.924**	2.419***
	(0.0499)	(0.0232)	(0.0499)	(0.0231)	(0.591)	(0.285)
Work experience			0.0432***	0.0330***		
			(0.00209)	(0.00216)		
Educational level			0.0821***	0.0440***		
			(0.00695)	(0.00793)		
Number of skills (log)			0.0792***	0.0282**		
			(0.0203)	(0.00986)		
Observations	10927362	7927294	10851657	7873046	10569121	7633972
R^2	0.215	0.612	0.218	0.613	–0.013	–0.021
Fixed effects:						
Occupation × Country × Year	Yes		Yes		Yes	
Occupation × Employer × Country × Year		Yes		Yes		Yes
Job portal		Yes		Yes		Yes

* $p < .05$; ** $p < .01$; *** $p < .001$

• Standard errors are in parentheses. All models are clustered at the firm level.

Table 4, Models 3 and 4, include qualifications and skill requirements as control variables. In our strictest model specification, adding requirements for work experience, education credentials, and the number of skills reduces the positive association between remote work and wages by about 5 percent. While this reduction may seem modest, it is notable given that job postings capture only a portion of employers' actual expectations. The three variables—required work experience, education credentials, and the number of skills—likely represent only a fraction of the broader differences in hiring requirements between remote and in-person jobs.

Finally, Models 5 and 6 in Table 4 use the interaction between a country's social distancing stringency index and an occupation's teleworkability as an instrument for remote work. Results from this IV approach show that remote work increases wages by 0.6–0.7 standard deviations. Overall, these findings suggest that remote work not only raises skill and qualification requirements but also leads to higher wages.

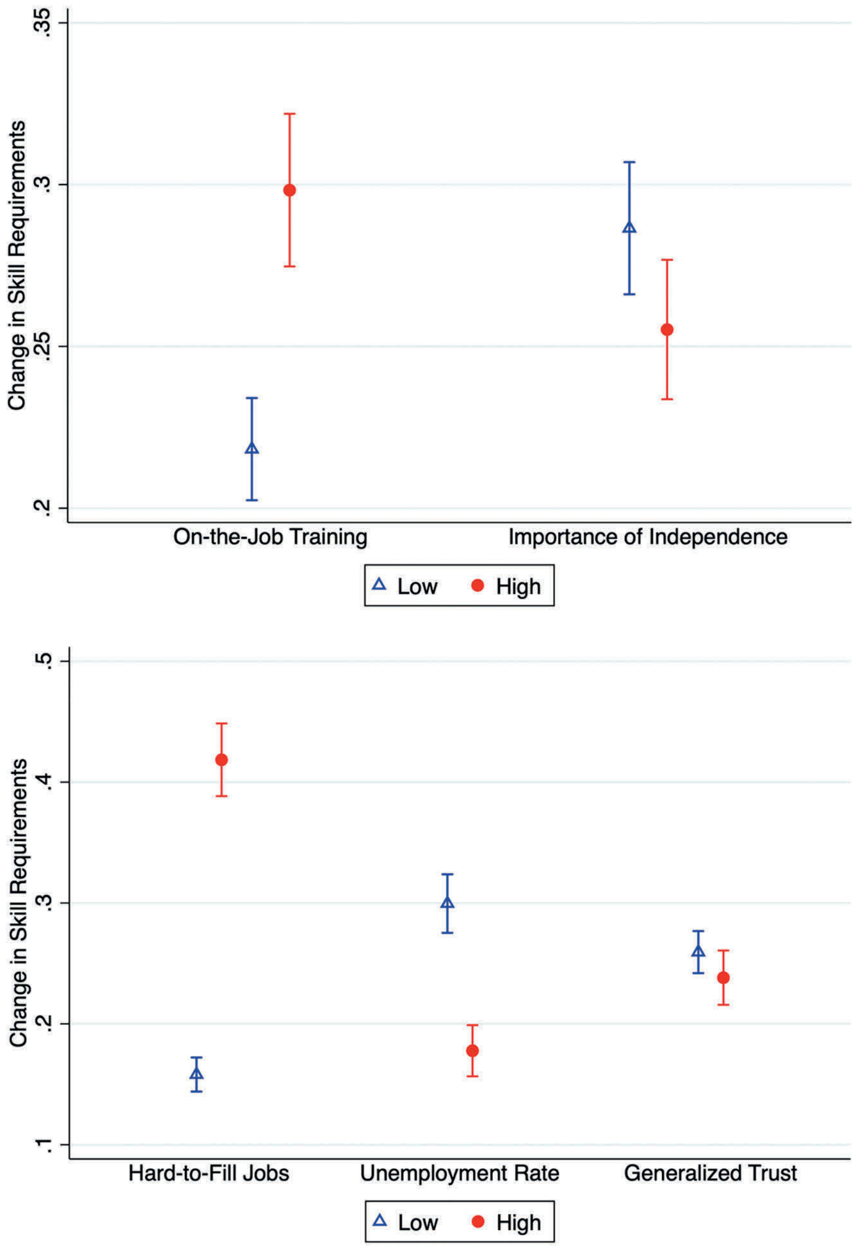
MECHANISMS

Several potential mechanisms could explain the elevated skill requirements observed in remote work. While we cannot definitively confirm or exclude any specific mechanism, we conducted multiple analyses to examine the presence or absence of each, which provides insights into their plausibility.

On-the-Job Training

Our first mechanism examines the challenges of training remote workers, particularly for jobs requiring significant on-the-job training. The Bureau of Labor Statistics (BLS) provides an on-the-job training score for each occupation, which

Figure 5. Testing Mechanisms: Different Moderators•



• The figures show the estimated coefficients for remote work in predicting the logged number of required skills under different conditions. Results with the full interaction terms are presented in Online Appendix Table L.1. The figures display estimated coefficients for remote work at both high and low levels of each moderator, where the moderating variable is set at one standard deviation above or below the mean. The five moderators include an occupation's on-the-job training score, its independence score, a firm–occupation's time to fill a job, a region–year's unemployment rate, and a country's generalized trust.

reflects the minimum training needed after hiring for an employee to perform their job effectively. This score is derived from nationally representative employer surveys across industries. Detailed definitions and methodology are available in Online Appendix Section J. Importantly, the on-the-job training measure captures all training conducted post-hiring, whether remote or in person, and has a weak correlation (–0.25) with an occupation's teleworkability.

We used a crosswalk between Standard Occupational Classification codes from BLS and ESCO occupation codes used by Lightcast to access the training requirements for each occupation in our dataset. Consistent with this mechanism, Online Appendix Table L.1 shows that interacting on-the-job training and remote work produces a strong positive coefficient: Remote work is associated with higher skill expectations and qualifications when the job requires more on-the-job training. In Figure 5, using the strictest fixed effects model specification, for a job that requires high on-the-job training (one SD above the mean), remote work predicts a 35 percent increase in skill count. When a job requires low on-the-job training (one SD below the mean), remote work predicts only a 25 percent increase in skill count. This analysis suggests that the skill gap between remote and in-person jobs is much more pronounced for jobs requiring more on-the-job training.

On-the-Job Support

A related mechanism is the challenge of providing on-the-job support to remote workers, which is likely greater in jobs that require more interdependence. In highly interdependent jobs, this difficulty of on-the-job support could lead employers to have different hiring expectations for in-person versus remote roles. However, this difference may be less noticeable in jobs that involve more independence, for which on-the-job support is less critical. The BLS measures job independence in its O*NET database, which we matched to our ESCO occupation codes to assess how independence moderates the relationship between remote work and skill requirements. In Online Appendix Table L.1, the elevated skill requirements for remote work are slightly less pronounced in jobs with higher independence. Figure 5 shows that in occupations with low independence (one standard deviation below the mean), remote workers are expected to possess 34 percent more skills, compared to their non-remote counterparts. In occupations with high independence (one standard deviation above the mean), the skill differences between remote and non-remote work are smaller, at 30 percent.

Expanded Applicant Pool

Another mechanism is the expansion of the applicant pool for remote positions, enabled by the removal of geographic constraints and the attractiveness of remote work to many candidates. Although we do not have direct data on applicant pool size for each position, we used two indirect measures as proxies.

The first proxy for applicant pool size is the time a firm typically takes to fill a particular position. Positions that take longer to fill likely suffer from smaller applicant pools and stand to benefit more from the expanded pool offered by remote work. Using our job posting data, we measured how long an in-person job posting remains active before being taken down. Specifically, we calculated, as a measure of demand, the average number of days a firm posted a job before COVID-19; we aggregated that measure to the occupation–firm level and added it as a moderator in our analysis. As shown in Online Appendix Table L.1, the positive association between remote work and skill requirements is much stronger for jobs that traditionally take longer to fill. In Figure 5, for positions with longer time-to-fill durations (one standard deviation above the mean), remote work significantly expands the applicant pool, leading to a 52 percent increase in skill requirements. In contrast, for jobs for which the supply of qualified workers is relatively high and positions tend to be filled quickly (one standard deviation below the mean time-to-fill), the difference in skill requirements between remote and in-person jobs is only 21 percent.

The second proxy is the local labor market's unemployment rate. Higher unemployment rates indicate a larger pool of job seekers, which could reduce the value of an expanded applicant pool in remote work. We used the unemployment rate at the NUTS-2 (Nomenclature of Units for Territorial Statistics) regional level, substituting with NUTS-1 rates (from larger regions) if NUTS-2 data were unavailable, and with national rates if neither was available. As shown in Online Appendix Table L.1, the relationship between remote work and skill expectations is less pronounced in regions with high unemployment. In such areas (one SD above the mean), where the local applicant pool is presumably larger, the difference in skill expectations between remote and in-person jobs is only 20 percent, as shown in Figure 5. However, in regions with low unemployment (one SD below the mean), the difference increases to 35 percent. Alternatively, analyzing a region's labor force participation rate instead of the unemployment rate yields substantively similar conclusions.

Emphasis on Measurable Qualities

A third distinct mechanism is that remote work, due to challenges in building trust and monitoring performance, may lead employers to prioritize workers with more-quantifiable metrics, such as skills and credentials, over less-tangible traits like cultural fit and work attitude. Directly testing this mechanism is challenging, as these preferences often occur internally within employers' decision-making processes. However, we explored potential indirect evidence to assess this mechanism. While some evidence that we present here is consistent with this explanation, much of it is not.

First, we examined the types of skills that employers prioritize in remote versus in-person jobs. If this mechanism holds, we would expect a shift toward more-quantifiable and measurable skills in remote work. To test this, we used GPT-4 to rate all ESCO skills on a measurability scale, with higher scores indicating skills that are clearer, more measurable, and more objective. As shown in Online Appendix Table L.2, employers are no more likely to require measurable skills for remote positions than for in-person roles, providing little support for this mechanism.

Second, we examined whether employers hiring for remote work are less likely than employers hiring for in-person roles to emphasize firm culture. Our qualitative evidence suggests that employers hiring for remote roles focus less on culture and trust in the workplace than do employers hiring for in-person roles. However, job postings do not reflect this pattern. Employers hiring for

Table 5. Summary of Proposed Mechanisms

Proposed Mechanisms	Brief Explanations	Evidence
Difficulty of on-the-job training	Remote work limits training opportunities, requiring workers to possess necessary skills upfront.	The effect is stronger for jobs that require more on-the-job training.
Difficulty of on-the-job support	Remote work hinders supervision and support, requiring workers to have greater independence and problem-solving skills.	The effect is slightly weaker for jobs that require more independence.
Expanded applicant pool	More people apply to remote positions due to (1) fewer geographic constraints and (2) the broader appeal of remote work, leading to higher job requirements.	The effect is weaker in areas with higher unemployment and lower labor force participation, as an expanded applicant pool likely has less impact in these regions. The effect is stronger for harder-to-fill jobs, which should benefit more from an expanded applicant pool.
Emphasis on measurable qualities	(1) Building trust is more challenging, and (2) intangible traits like fit and dedication are harder to evaluate, leading employers to focus on measurable metrics like skills and qualifications.	The effect is stronger in lower-trust countries, although evidence on this is mixed. Remote jobs are just as likely to emphasize organizational culture and list specific requirements, which is inconsistent with this mechanism.

remote positions are just as likely to mention culture-related keywords as are those hiring for in-person roles.

Finally, the shift toward more-quantifiable metrics in remote work may be driven by the challenges of building trust and monitoring performance, which are likely more pronounced in lower-trust contexts. To test this, we used a country's generalized trust level as a moderator. As shown in Figure 5, employers in high-trust countries require 27 percent more skills for remote positions than for in-person roles, while in low-trust countries, this difference increases to 30 percent. These differences across trust levels align with this mechanism. However, when using bilateral trust between countries to analyze multinational firms based on their headquarters and hiring locations, we did not find that bilateral trust moderates the main relationship in the expected direction.

On balance, the patterns appear more consistent with training/support frictions and an expanded labor pool than with a shift toward measurable qualities. The remote premium grows where on-the-job training demands are higher and roles are harder to fill—settings in which firms typically rely more on post-hire learning and support, and where larger pools of potential applications allow firms to be more selective and set higher requirements. By contrast, the evidence for a shift toward more measurable qualities is mixed. One possibility is that firms can mitigate trust and monitoring concerns through hiring processes (e.g., trials or work samples) but cannot as easily replicate tacit training and support in remote settings. Table 5 summarizes these mechanisms and the corresponding evidence.

Alternative Explanations

There are a few additional explanations that may contribute to our observed patterns. One is the complete contract explanation, which suggests that employers hiring for remote positions may feel a greater need to explicitly outline terms and responsibilities than do employers hiring for in-person positions. This explanation differs from the mechanism above in that the differences between remote and in-person jobs would mainly appear in job postings rather than in the actual job requirements. In our data, remote job postings tend to be longer, which is consistent with this explanation. However, longer postings could also indicate higher skill requirements, making it difficult to distinguish between these mechanisms.

A few additional analyses help to ensure that our findings are not solely driven by the complete contract explanation. First, even after we controlled for job posting length and its variations, the positive association between remote work and skill requirements remains substantial (see Online Appendix Table I.6). Second, when we looked at the actual number of years of work experience required—rather than just whether work experience is mentioned—we still find a clear difference, which should not be affected by this explanation. Third, as already mentioned above, we do not find that job postings for remote work require more-specific and less-ambiguous skills than do job postings for in-person roles. While these analyses do not entirely rule out the complete contract explanation, they suggest that much of the observed effect is not driven by it.

Another plausible explanation is the first-stage screening hypothesis: Anticipating a larger applicant pool, employers hiring for remote work may list higher skill requirements and qualifications in job postings to streamline initial screening, though these elevated criteria may not ultimately influence final hiring decisions. However, we observed a noticeable wage increase in remote work, which contradicts the first-stage screening explanation. If employers were merely inflating skill requirements to filter candidates but not applying those higher standards in final hiring, we would not expect to see higher wages. The wage increase suggests that employers are genuinely seeking higher-skilled workers for remote positions.

A third alternative explanation is that our findings reflect changes in organizational structure or task composition. Remote work may prompt firms to restructure roles or adjust tasks, and these shifts could raise skill requirements. We addressed this concern in two ways. First, we included employer–job-title fixed effects, which focus the analysis on variation within the same employer and job title (see Online Appendix Table I.1). Because task content is unlikely to vary much within a given job title, this approach reduces the influence of structural change. Second, we included fixed effects for job tasks to account for possible variation in task content (see Online Appendix Table I.2). Even after applying these controls, we continued to observe elevated skill requirements. This pattern suggests that organizational restructuring or task changes alone cannot explain the results.

Finally, we conducted several additional analyses to address potential concerns, as detailed in Online Appendix Section I. These included testing different

[5] The study was reviewed and approved by the Institutional Review Board at Northeastern University (IRB 23-07-01: "remote work and hiring requirements").

model specifications, incorporating finer geographic fixed effects at the employer–region–occupation level, and replicating results using the pre-COVID sample.

AN ONLINE EXPERIMENT

We conducted a preregistered online experiment to supplement our main findings. The purpose of the experiment was to establish stronger causal inference. Our overall design was to recruit online participants with hiring experience to specify their hiring requirements for a randomly assigned job (either remote or in person).[5]

We conducted our experiment on Prolific Academic (http://www.prolific.co), an online survey platform with a demographically diverse pool of over 100,000 respondents. An a priori power analysis conducted using G*Power (Faul et al., 2007) determined that a sample of 1,199 participants was needed to achieve 80 percent power at an alpha level of 0.05 with a small-to-medium effect size ($f^2 = 0.10$). To align with the geographic distribution of our main study, we recruited full-time employees with hiring experience from the 28 EU countries. To ensure high-quality data, only participants with a 95 percent or higher approval rate and at least 50 prior study participations on Prolific were invited. We ultimately collected 1,406 responses.

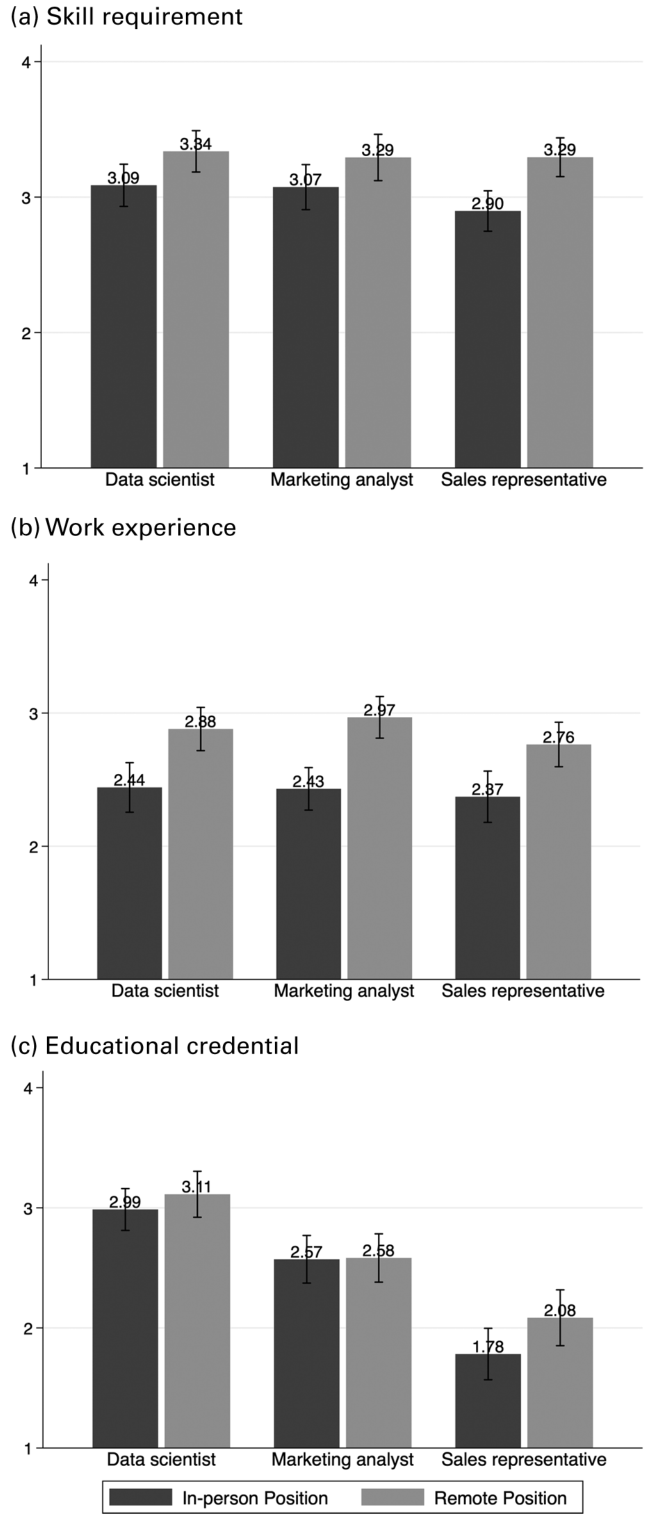
To ensure data quality, we included attention-check questions. Participants who completed the experiment unrealistically quickly (under one minute, n = 1) or failed comprehension checks (e.g., recalling their assigned occupation or remote/onsite condition, n = 145 total) were excluded. Additionally, participants who self-reported unreliable responses (n = 10) were removed. After we applied all data-screening criteria, 1,250 valid responses remained for analysis. The median response time was 3:52 minutes, and participants were compensated 0.8 USD. The majority were from the United Kingdom, Poland, Italy, and Germany, with 44 percent identifying as women and 90 percent holding a college degree or higher. The median age range was 36–45 years, and participants had a median of 4–6 years of hiring experience. Most (65 percent) had experience hiring for remote positions. Detailed participant demographics are provided in Online Appendix Table M.1.

Participants were presented with a real company scenario to simulate a realistic hiring task. We partnered with a New England–based semiconductor manufacturer, established five years prior to the experiment, with European offices. Participants were informed that their input would help the company set hiring criteria, making the task feel meaningful.

We used a 2 × 3 × 3 experimental design, manipulating work setting (remote vs. onsite), qualifications (skills, work experience, or education level), and job roles (data scientist, marketing analyst, or sales representative). We chose these job roles because they are common non-manual roles that vary widely in skill requirements and are frequently performed in both remote and in-person settings. This variation allowed us to examine how remote work influences hiring expectations across different types of job functions, while maintaining relevance across industries.

Participants were randomly assigned to one of 18 conditions. For example, a remote data scientist job description reads as follows: ‘‘We are trying to hire a data scientist. A potential candidate can work with our data team for both

Figure 6. Supplementary Analyses: An Online Experiment•



•The figure shows descriptive results from our online experiment. All three variables—number of skills, work experience, and education level—are on a four-point scale.

Table 6. Supplementary Analysis: An Online Experiment•

	Skill Requirement (1)	Work Experience (2)	Educational Credential (3)
Remote work	0.289***	0.454***	0.147
	(0.0649)	(0.0712)	(0.0842)
Observations	412	419	419
R^2	0.052	0.093	0.227
Fixed effects:			
Occupation	Yes	Yes	Yes

*$p < .05$; ** $p < .01$; *** $p < .001$
•Standard errors are in parentheses. The table shows OLS estimates from our online experiment. Participants were asked to recommend hiring requirements for three positions, with each position randomly assigned to be either remote or in-person. All models are clustered at the participant level.

scientific and commercial research. This position is a remote position. The worker can work anywhere in the world.''

Each participant rated qualifications on a four-point scale. Skill levels ranged from no prior skills to all relevant skills; work experience spanned from no prior experience to over five years; and education levels ranged from high school to graduate degrees. Participants selected the qualification they considered most important for the assigned position. Finally, participants provided demographic information, including gender, age, education, years of hiring experience, country, industry, occupation, and remote hiring experience. Online Appendix Figure M.1 shows the full survey.

Experimental Results

The experimental results indicate that participants recommend higher skills and more years of work experience for remote positions than for in-person roles. Figure 6 illustrates these differences in hiring requirements. Participants did not suggest a significant difference in education credentials between remote and in-person positions.

The results are also broken down by job roles: data scientists, marketing analysts, and sales representatives. Notably, participants recommended more skills for remote sales representative positions than for the other roles, likely because sales roles typically require more on-the-job training and support, which may be harder to provide in remote settings. In contrast, technical roles like data scientists and marketing analysts are more adaptable to remote work, due to their reliance on specialized skills. However, across the three positions, no notable differences were observed in the years of work experience or education requirements recommended by participants.

In Table 6, the OLS models include fixed effects for position and cluster the standard errors by participant. The results align with the findings in Figure 6: Remote work increases hiring requirements for the number of skills by 0.43 standard deviations and for work experience by 0.59 standard deviations. Remote work does not predict a statistically significant increase in education credentials. These results provide stronger causal validity for our main estimates derived from the job posting data.

DISCUSSION AND CONCLUSION

This study suggests that remote positions are associated with higher requirements for skills and qualifications. We began with in-depth qualitative interviews and proposed several mechanisms that predict this pattern, before analyzing 50 million job postings from 28 EU countries to support our hypotheses. Additional analyses indicate that these higher requirements may reflect the challenges of training and supporting employees at a distance, as well as the larger pool of applicants for remote positions.

Contribution to the Hiring Literature

Existing research has largely explained rising skill requirements through automation, globalization, and institutional change, with skill-biased technological change providing a particularly influential framework (e.g., Acemoglu & Autor, 2011; Autor et al., 2003). Yet, this prior research has focused primarily on how technology alters the tasks that workers perform. Our study highlights a different channel: changes in work arrangements. With advances in digital communication, remote work has become increasingly feasible. It reshapes how employees interact, how trust is established, and how organizations access labor markets.

We show that remote jobs are associated with higher requirements for skills and work experience, and we propose several mechanisms that help to explain why: the difficulty of training and supporting workers at a distance, an expanded pool of applicants that allows employers to raise standards, and stronger reliance on measurable qualifications when trust is harder to build. By pointing out these mechanisms, our study expands the hiring literature beyond task change to demonstrate how the structure of work arrangements can also drive job upgrading.

These findings carry important implications for workers, firms, and policymakers. Remote arrangements may amplify existing inequalities by privileging those with prior experience and access to skill development. If remote work shifts training costs to workers, early-career individuals may face greater barriers to entry. In traditional in-person settings, firms often invest in developing less-experienced employees through mentoring and informal learning. When such learning becomes more difficult in remote environments, employers may prefer candidates who already possess demonstrable skills and experience.

Contribution to the Remote Work Literature

Many studies have examined how remote work affects productivity, with mixed findings. Some studies report productivity gains (e.g., Bloom et al., 2015; Choudhury et al., 2021), while others document declines, particularly for call center workers, technology professionals, and creative roles (Emanuel & Harrington, 2024; Gibbs et al., 2023; Yang et al., 2022). Evidence also suggests that hybrid work can outperform pure remote arrangements by improving both productivity and novelty of output (Choudhury et al., 2021).

Another stream of research considers well-being and job satisfaction, with no clear consensus. Some studies suggest that remote work reduces stress

(Gajendran & Harrison, 2007), while others find negative effects, especially for parents and women, including lower happiness and greater work–life conflict (Chung & van der Horst, 2018; Glass & Noonan, 2016; Kelliher & Anderson, 2010).

Our study focuses on the relationship between remote work and the labor market. The closest literature is a set of studies on the career implications of remote work. This line of work shows that remote workers often face reduced promotion opportunities (Bloom et al., 2015; Emanuel & Harrington, 2024), in part because in-person work provides more chances for bonding and informal interactions. Recent evidence shows that physical proximity increases feedback and improves performance, particularly for less-experienced workers who are building human capital (Emanuel et al., 2023).

Our study shifts the focus from worker outcomes to employer behavior, and we examine how remote work shapes hiring expectations. We show how several mechanisms—the challenges of providing training and support, the expansion of the applicant pool, and a stronger reliance on measurable qualifications—can lead to higher skill requirements. By linking remote work to hiring demand, we extend the literature on remote work to the front end of the labor market.

Limitations and Future Research

Several limitations of this study provide opportunities for future research. First, job postings provide only the employer's perspective. They reflect employers' hiring expectations, but we do not know who employers end up hiring. While this article establishes the relationship between remote work and employers' hiring requirements, future research could do more to examine the types of candidates that remote work attracts and hires. For example, are people with higher education actually more likely to work in remote positions? Does remote work attract certain demographics? One possibility is to merge the job advertisement data with employer–employee linked datasets in the EU. Although such mergers would be labor-intensive, they could help us answer many interesting and important questions about worker characteristics.

Second, there may be unobserved heterogeneity. Although we used strict fixed effects, an instrumental variable strategy, and a lab experiment, we could not fully separate remote adoption from broader changes in job design that occurred during the pandemic. Remote work may have coincided with restructuring, task reallocation, or shifts in managerial practices that are difficult to observe in job posting data. Future research could address this limitation by exploiting pre-pandemic instruments, policy discontinuities unrelated to COVID, or richer task-level and within-firm panel data to isolate variation in work arrangements more precisely. Linking job postings to employer–employee matched data would also help distinguish changes in screening standards from changes in actual job content.

Third, our findings capture a dynamic shaped by the current state of telecommuting technologies and labor market conditions. As new virtual communication tools, collaboration platforms, and work processes emerge, remote work may become more synchronous and offer greater opportunities for informal social interaction. These advancements could eventually bring hiring expectations for remote and non-remote work into closer alignment. Despite these potential changes, we believe that remote work will continue to shape employers' hiring expectations in the near future.

Today's workplace spans office and home. The shift is more than geographic—it is reshaping interaction patterns and labor mobility, and it is rewriting hiring norms by raising skill expectations.

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Data Availability Statement

The data used in this study are proprietary and were obtained from Lightcast under a licensing agreement. As such, the raw data cannot be publicly shared. The code used for analysis is available on the authors' personal websites.

Supplementary Material

Supplementary material for this article can be found in the Online Appendix at http://journals.sagepub.com/doi/suppl/10.1177/00018392261450609.

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