Online Appendices for

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

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Appendix Section A. Interview Protocol

Introductory Protocol

We conducted semi-structured interviews with managers and hiring decision-makers involved in recruitment and personnel management. The purpose of the interviews was to understand how remote, hybrid, and in-person work arrangements shape hiring practices and organizational expectations.

At the beginning of each interview, participants were informed about the purpose of the study and the voluntary nature of participation. We asked for permission to audio-record the interview to facilitate accurate transcription. Interviews were recorded only when participants provided explicit consent; when recording was declined, detailed notes were taken during the interview and expanded afterward. All participants are anonymous in the current manuscript, and any identifying information has been removed. All materials were used solely for research purposes and stored securely. Interviews lasted approximately 30–60 minutes.

The questions below served as a guide. Follow-up questions were asked when relevant based on participants' responses and roles, including requests for clarification, examples, or further elaboration.

A. Interviewee Background

1. Can you briefly describe your current role and responsibilities in the organization?

B. Organizational Context

1. What is your organization's current approach to remote, hybrid, or in-person work?
2. How has this approach evolved over time?

C. Hiring and Recruitment

1. Can you walk me through how your organization typically hires for a position?
2. What factors are most important when evaluating candidates for remote positions?
3. Have you observed differences in the applicant pool for remote versus in-person roles?
4. In your experience, are there differences in the types or quality of candidates hired for remote versus in-person positions?

D. Work Practices

1. Are there differences in onboarding processes for remote versus in-person employees?
2. From your perspective, how does day-to-day work differ between remote and in-person settings?
3. Is there anything else about remote work and hiring practices that you think is important for us to understand?

Appendix Section B. Background Information of Interviewees

Table B.1: Interviewee Background

Respondent ID	Work Experience (Years)	Start Year	Job Title	Employer Size	Industry	Experience Level
R1	6	2018	Human Resources Manager	2500-3000	Automotive	Early Career
R2	28	1996	Managing Director	20-30	Computer Hardware	Senior-Level
R3	13	2011	Head Of Sales And Marketing	500-1000	Computer Hardware	Mid-Level
R4	24	2000	Senior Sales Manager	30-40	Computer Hardware	Senior-Level
R5	21	2003	Global Head Of Human Resources	300-400	Computer Software	Senior-Level
R6	29	1995	Chief Technology Officer / Vice President	20-30	Computer Software	Senior-Level
R7	21	2003	VP Of HR	100-200	Computer Software	Senior-Level
R8	20	2004	Manager Resource Management Americas Lead	11000-12000	Computer Software	Mid-Level
R9	27	1997	Senior Human Resources Manager	6500-7000	Construction	Senior-Level
R10	21	2003	Founder	20-30	Design	Senior-Level
R11	15	2009	Human Resources Manager	100-200	Design	Mid-Level
R12	7	2017	Human Resources Manager	100-200	Electrical/Electronic Manufacturing	Early Career
R13	27	1997	Vice President	200-300	Electrical/Electronic Manufacturing	Senior-Level
R14	25	1999	Manager Of Operations and Human Resources	800-900	Entertainment	Senior-Level
R15	7	2017	Research Analyst	30-40	Financial Services	Early Career
R16	7	2017	Human Resources Manager	100-200	Food & Beverages	Early Career
R17	19	2005	Human Resources Manager	50-60	Food & Beverages	Mid-Level
R18	9	2015	Human Resources Manager	300-400	Food & Beverages	Early Career
R19	25	1999	Human Resources Manager	100-200	Food & Beverages	Senior-Level
R20	22	2002	Human Resources Manager	3500-4000	Government Administration	Senior-Level
R21	33	1991	Managing Partner	10-20	Investment Management	Expert/Executive
R22	33	1991	Managing Director	1-10	Investment Management	Expert/Executive
R23	12	2012	Managing Partner	1-10	Investment Management	Mid-Level
R24	27	1997	Managing Director	100,000+	Management Consulting	Senior-Level
R25	44	1980	Managing Director	9500-10000	Management Consulting	Expert/Executive
R26	30	1994	Human Resources Manager	200-300	Mental Health Care	Senior-Level
R27	6	2018	Human Resources Manager	50-60	Museums and Institutions	Early Career
R28	25	1999	NY - UN Correspondent	200-300	Newspapers, Online Media	Senior-Level

Continued on next page

R29	25	1999	Human Resources Manager	100-200	Non-profit Organizations	Senior-Level
R30	8	2016	Chief Executive Officer	10-20	NonProfit Organization Management	Early Career
R31	22	2002	Senior Human Resources Business Partner	20000-21000	Outsourcing Offshoring	Senior-Level
R32	39	1985	Founder & Managing Director	20-30	Professional Training & Coaching	Expert/Executive
R33	23	2001	Managing Director	200-300	Public Relations and Communications Services	Senior-Level
R34	18	2006	Director Of Human Resources And Talent Management	400-500	Religious Institutions	Mid-Level
R35	9	2015	Human Resources Manager	50-60	Renewables & Environment	Early Career
R36	27	1997	Sr. Product And Technical Marketing Manager	11000-12000	Semiconductors	Senior-Level
R37	14	2010	USA HQ Corporate Account Manager	1500-2000	Transportation	Mid-Level

Appendix Section C. Online Job Vacancy Collection Process

Lightcast collaborated with the European Centre for the Development of Vocational Training (Cedefop) to collect online job postings across the European Union. The data collection process involves several steps.

First, the research team identifies potential job vacancy portals. These websites are evaluated based on factors such as how frequently job postings are updated, the range of industries and locations covered, and whether the listings follow a structured format. About 300 sources were selected, covering more than 60,000 websites. Some sources, such as job aggregators, link to hundreds or even thousands of individual company websites where the actual job postings appear. The selection includes job search engines, public employment services, recruitment agency websites, and other platforms like online newspapers. The role of these sources varies by country—public employment services, for instance, play a smaller role in Ireland, Italy, and the UK compared to countries like the Czech Republic, Germany, Spain, and France. Experts familiar with EU job markets finalize the selection of job boards (Cedefop, 2019).

The data collection process uses various methods, including API access, web crawling, and web scraping, depending on whether direct database access is available. Job portal owners are informed about the data collection effort, and whenever possible, formal agreements are made to ensure cooperation between Cedefop and the platform owners. Direct API access is preferred, but when it is not an option, web scraping and crawling techniques are used instead.

After collecting the data, the language of each job posting is identified, regardless of the website it came from. This ensures that job postings can be processed in all official EU languages, as well as other commonly used languages such as Catalan, Basque, Gaelic, and Russian.

The quality and content of job postings vary across sources, so a pre-processing step is necessary to create a consistent database for analysis. This process includes cleaning the data, merging duplicate postings, and removing redundancies. The cleaning step involves removing irrelevant information such as advertisements and unselected options from dropdown menus to ensure the dataset contains only relevant and accurate details. Merging is important because employers often post the same job on multiple platforms. While duplicate listings are removed before final analysis, merging them at an earlier stage helps combine information from different versions of the same posting. After merging, the research team conducts a de-duplication process, flagging a job posting as a duplicate if it shares the same description and location as another listing in the database. Additional metadata, such as reference IDs and page URLs, help detect and remove duplicates, particularly on aggregator websites.

The final step is to extract and classify job information using a combination of ontologies and machine learning models. Ontologies provide a structured framework for analyzing job postings, covering key aspects such as occupation titles, industries, regions, and contract types. The research team first attempts to classify job information through text matching or similarity with these ontologies. Job postings are processed in their original language to ensure accurate classification. If no match is found, a machine learning algorithm is used to assign the most appropriate category. These algorithms match job advertisement content to terms within the ontologies, such as linking vacancy titles to ESCO occupations or required skills to ESCO skill classifications. The accuracy of this automated classification is regularly reviewed by experts, who provide feedback and suggested corrections to improve the machine learning process.

One potential concern is that job postings may differ across platforms due to

platform-specific rules, which could affect our analysis. For example, remote jobs may be more likely to appear on larger platforms within each country. To account for this, we include job portal fixed effects to isolate unobserved platform effects. We also conducted a descriptive comparison of jobs posted on large, medium, and small portals. As shown in Appendix Figure C.1, there is no clear pattern in the number of required skills, years of work experience, education levels, or the proportion of remote jobs across platforms of different sizes.

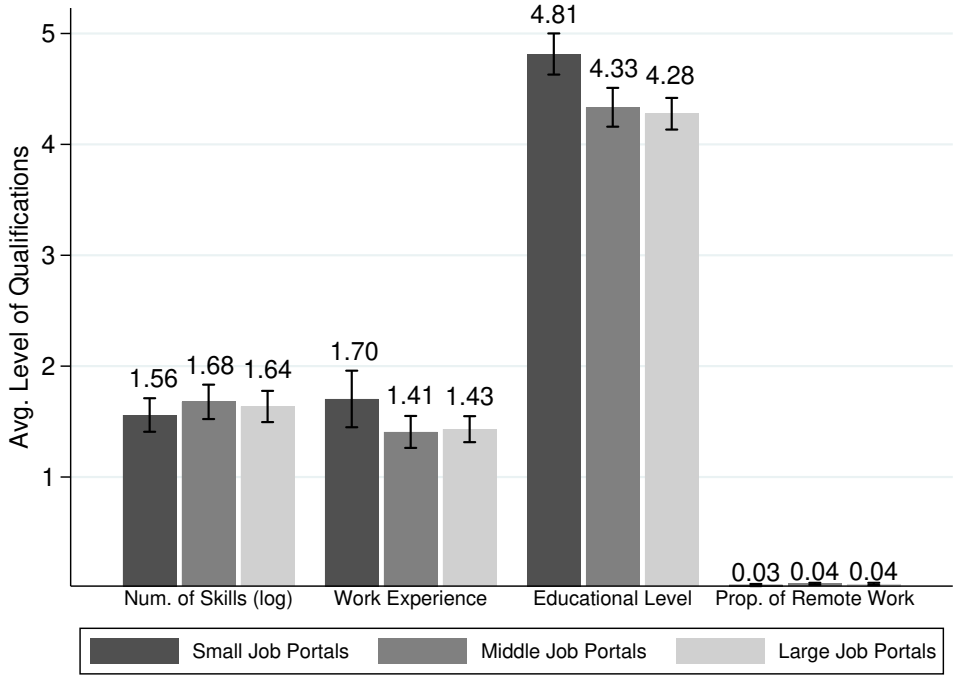


Figure C.1: Descriptive Figure: Job Requirements by Job Portals

Appendix Section D. Sample Distribution

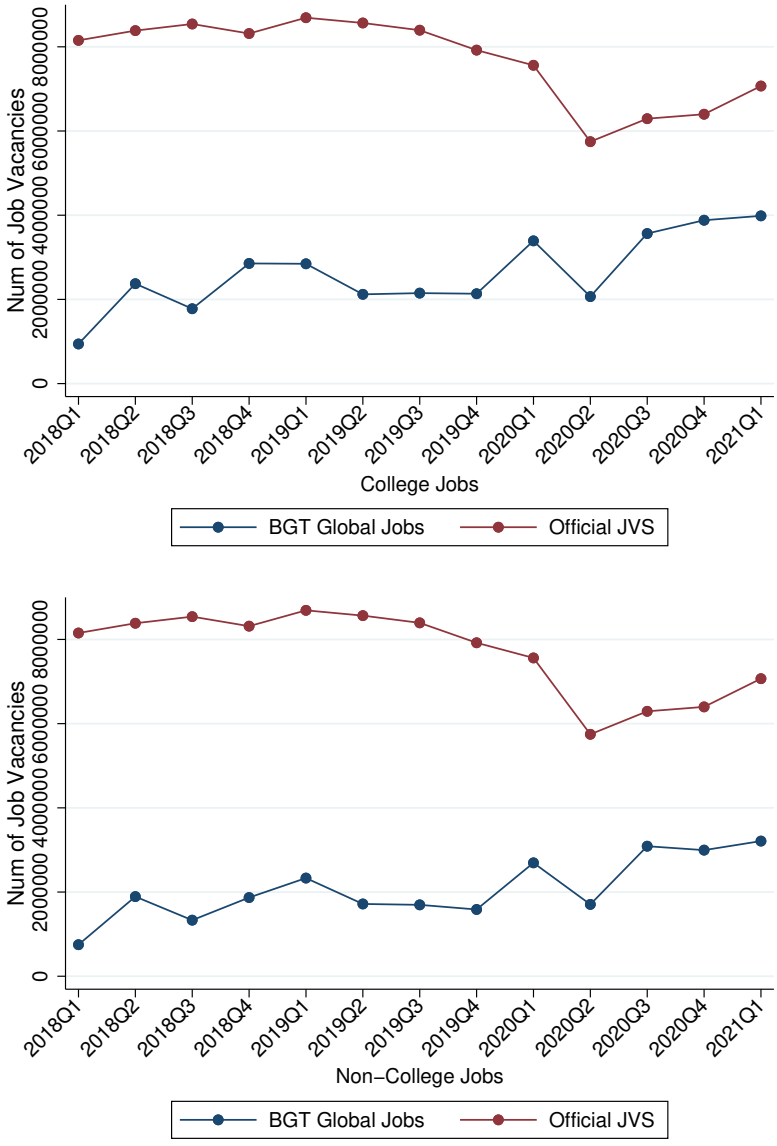


Figure D.1: Number of Job Postings by Quarter

Notes: The figures compare the number of job postings in the Lightcast sample and the number of job openings from Job Vacancy Statistics provided by Eurostat. We separate high-skilled jobs from low-skilled jobs in Lightcast. The former includes managerial and professional positions and the latter includes the rest. Job vacancy information in JVS is derived using employer surveys and could underestimate the total number of job vacancies because it does not cover many small employers. We aggregate data across the 28 EU countries and plot the numbers quarter by quarter.

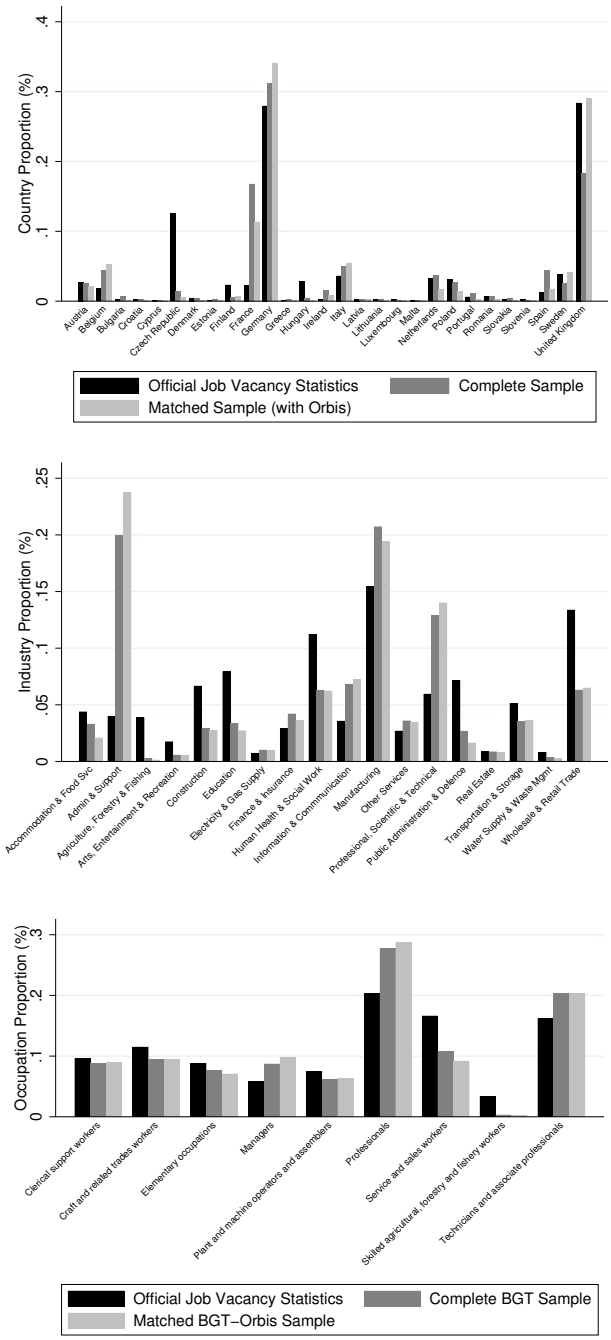


Figure D.2: Sample Distribution by Country, Industry and Occupation

Notes: We compare the country, industry and occupation distribution of Lightcast job postings to that of official employment statistics. These three barplots show the country, industry, and occupation distribution for our job-posting data. The original Lightcast sample contains all job postings in 28 European countries, 2018–2021. The matched sample contains postings that are matched with Bureau Van Dijk's Orbis database. Official employment statistics come from OECD Statistics and the International Labor Organization. These are generally based on representative surveys of households in each country. The y-axis shows the proportion of the sample accounted for by each country, industry, and occupation.

Table D.1: Number of Job Postings, Sorted by Country

	Complete Sample	Valid Sample
Austria	1,371,833	1,370,925
Belgium	3,069,948	3,012,678
Bulgaria	361,137	360,699
Croatia	124,003	123,930
Cyprus	27,835	27,740
Czech Republic	509,239	508,675
Denmark	71,028	71,002
Estonia	160,032	158,496
Finland	282,364	280,439
France	10,992,257	10,969,386
Germany	18,267,440	12,301,319
Greece	140,525	139,830
Hungary	181,070	44,119
Ireland	911,670	911,497
Italy	4,666,598	3,205,594
Latvia	135,813	19,234
Lithuania	213,937	213,246
Luxembourg	66,113	66,088
Malta	18,157	18,147
Netherlands	2,284,906	2,249,376
Poland	1,199,517	1,199,257
Portugal	617,027	616,159
Romania	293,750	293,527
Slovakia	111,223	111,208
Slovenia	78,947	78,845
Spain	2,925,078	2,922,690
Sweden	1,528,033	1,525,017
United Kingdom	11,936,300	8,952,549
Total	62,545,780	51,780,967

Notes: The complete sample includes all job postings collected by Lightcast across the 28 European Union countries between 2018 and 2021, excluding postings with missing firm information. The valid sample further restricts to postings with non-missing skill information, as skill requirements are the primary dependent variable in our analysis.

Table D.2: Major Online Portals Included in the Lightcast Sample

Country	Website	Country	Website
Austria	https://www.ams.at/	Ireland	https://www.irishjobs.ie/
	https://www.karriere.at/		https://www.simplyhired.com/
	https://www.simplyhired.com/		https://www.monster.ie/
	https://www.willhaben.at/jobs/		https://jobbio.com/
Belgium	https://www.vdab.be/		https://www.jobs.ie/
	https://europa.eu/eures/	Italy	https://www.infojobs.it/
	https://www.simplyhired.com/		https://www.monster.it/
	https://www.stepstone.be/		https://www.simplyhired.com/
	https://www.monster.be/		https://www.cliccalavoro.it/
Bulgaria	https://www.jobs.bg/		https://www.bachecalavoro.com/
	https://www.zaplata.bg/		
	https://europa.eu/eures/	Latvia	https://www.cv.lv/lv
	http://www.buljobs.bg/		https://www.visidarbi.lv/
Croatia	https://burzarada.hzz.hr/	Luxembourg	https://www.monster.lu/
	https://www.moj-posao.net/		https://en.jobs.lu/
	https://www.posao.hr/		https://www.careerjet.lu/
Cyprus	https://aggeliesergasias.com/	Malta	https://jobsinmalta.com/
	https://europa.eu/eures/		https://www.keepmeposted.com.mt/
Czech Republic	https://www.mpsv.cz/	Netherlands	https://www.simplyhired.com/
	https://prace.centrum.cz/		https://europa.eu/eures/
Denmark	https://www.jobindex.dk/		https://www.monster.nl/
	https://www.careerjet.dk/		https://www.uitzendbureau.nl/
	https://www.ofir.dk/		https://www.jobbird.com/nl
	https://europa.eu/eures/	Poland	https://www.pracuj.pl/
	https://www.randstad.dk/		https://praca.money.pl/
Estonia	https://www.tootukassa.ee/		https://www.careerjet.pl/
	https://www.cv.ee/	Portugal	https://emprego.sapo.pt/
	https://europa.eu/eures/		https://www.simplyhired.com/
Finland	https://europa.eu/eures/		https://www.buscojobs.com/
	https://www.oikotie.fi/		https://pt.jobrapido.com/
	https://www.careerjet.fi/	Romania	https://www.publi24.ro/
	https://duunitori.fi/		https://www.olx.ro/
France	https://www.pole-emploi.fr/accueil/		https://www.bestjobs.eu/
	https://www.simplyhired.com/	Slovakia	https://www.profesia.sk/
	https://www.jobintree.com/		https://www.istp.sk/
	https://europa.eu/eures/		https://www.careerjet.sk/
	https://www.apec.fr/	Spain	https://www.infojobs.net/
Germany	https://www.arbeitsagentur.de/		https://www.empleate.gob.es/
	https://www.xing.com/		https://www.simplyhired.com/
	https://www.arbeitsagentur.de/		https://www.careerjet.es/
	https://europa.eu/eures/	Sweden	https://jobtechdev.se/
	https://www.stepstone.de/		https://arbetsformedlingen.se/
Greece	https://www.skywalker.gr/		https://www.manpower.se/
	https://www.kariera.gr/		https://www.simplyhired.com/
	https://europa.eu/eures/	United Kingdom	https://www.reed.co.uk/
	https://www.careerjet.gr/		https://www.simplyhired.com/
Hungary	https://www.jobmonitor.com/		https://www.cv-library.co.uk/
	https://www.careerjet.hu/		https://www.monster.co.uk/
	https://www.jofogas.hu/		https://www.fish4.co.uk/

Notes: The table shows the major job portals in each country that Lightcast uses to collect job postings. It does not include all job portals; for larger economies like Germany and the United Kingdom, there are hundreds and we list only a few.

Appendix Section E. Coding Remote Work Dictionary

In this section, we detail the process of creating the remote work dictionary. First, we randomly selected 2,000 UK job postings from our dataset. We asked 5 research assistants to each read through 400 job postings and identify phrases indicating remote work settings. They were directed to focus on phrases rather than single words to avoid potential ambiguity. For example, ”remote” might relate to ”remote training” rather than actual ”remote employment.” The research assistants also compiled a list of phrases that could mistakenly suggest remote work, such as ”remote work: no.” to minimize the incidence of false positives. Our research assistants were not informed of our hypotheses; their task was solely to identify relevant phrases without considering job qualifications or skill requirements.

Second, we validated each identified phrase by assessing its occurrence across the full set of job postings. For every phrase, we randomly selected ten identified job postings to verify if the jobs were indeed remote. A phrase was included in our dictionary only if it correctly indicated remote work in at least 90% of cases. We excluded job postings containing any identified false positive phrases during this validation.

Next, to assess the accuracy of our dictionary-based approach, we compared it with alternative methods — manual review and GPT-4 models. We selected a random sample of 1,000 UK job postings and had two research assistants independently determine if each was a remote position. They were unaware of our hypotheses and the developed dictionary on remote work. They reviewed the text of postings and categorized each as ’1’ for remote or ’0’ for on-site. For those few postings where the research assistants reached different conclusions, we discussed them together and made a decision. Out of these, we identified 62 as remote and 938 as non-remote.

We then applied our remote-work dictionary to these 1,000 job postings. It identified 60 positions as remote, of which 57 were accurate, and 3 were false positives. To contrast, we processed the postings using the GPT-4 API. To this end, we submitted a batch of 1,000 job postings into the GPT-4 API using a specific prompt: ’Please read the following job posting, and identify whether this is a remote position or not. Please return in the following format (1=remote; 0=onsite): Remote work: .’ The responses were recorded in a variable named ’remote_work_gpt,’ which reflected whether the job was identified as remote by the GPT-4 model. The GPT-4 model flagged 60 postings as remote. Of these, 55 were validated as true remote positions, while 5 were inaccurately tagged, resulting in false positives. Additionally, the model overlooked 7 actual remote positions. Consequently, our dictionary-based approach showed higher accuracy, correctly classifying 99.2 percent of the job postings’ remote work status, thereby outperforming the GPT-4 models.

Appendix Table E.1 provides a detailed list of the remote work keywords and false positive keywords we include in the analysis. To save space, we only present these words in English, but in the analysis, we also include keywords in other official languages in the EU, including Bulgarian, Croatian, Czech, Danish, Dutch, English, Estonian, Finnish, French, German, Greek, Hungarian, Italian, Latvian, Lithuanian, Maltese, Polish, Portuguese, Romanian, Slovak, Slovenian, Spanish, Swedish, and Turkish. Beyond direct translations, we ask ChatGPT to tailor each phrase to reflect the vernacular of the local job markets, ensuring that our remote work dictionary accurately captures the commonly used expressions in regional job postings.

Table E.1: Remote Work Dictionary (English)

Remote Work Keywords	Remote Work Keyword — False Positive
(remote)	work from home no
100% remote	work remotely no
virtual office	remote working no
anywhere work	remote interview
completely remote	temporarily remote no
entirely remote	work from home is not
flexible location	not allow work from home
fully remote	remote work is not
geographically flexible	not allow remote work
home based	telecommuting is not
home office	not allow telecommuting
home-based work	virtual office is not
homebased	not allow virtual office
homeoffice	virtual work is not
location flexible	not allow virtual work
location remote	off-site work is not
location-independent	not allow off-site work
remote availability	work-from-anywhere is not
remote collaboration	not allow work-from-anywhere
remote company	virtual collaboration is not
remote employment	not allow virtual collaboration
remote environment	flexible work arrangement is not
remote flexibility	flexible work is not
remote job	not allow flexible work
remote location	distant work is not
remote office	not allow distant work
remote opportunity	off-site employment is not
remote option	not allow off-site employment
remote position	off-site employment is not
remote project	not allow off-site employment
remote role	
remote team	
remote work	
remote workforce	
remote working	
remote-based	
remote-friendly	
remotely	
smart working	
smartworking	
telecommut	
telecommute	
telecommuting	
telework	
virtual employment	
virtual position	
virtual team	
virtual work	
wfh	
work at home	
work from anywhere	
work from home	
work remotely	
working from home	
working remotely	

Appendix Section F. Coding Skill Requirements in Lightcast Job Postings

This section provides additional detail on Lightcast's skill coding procedure and its validation against O*NET ratings. Skill requirements are explicitly listed in most job postings; Appendix Figure F.1 provides representative examples. Lightcast's skill coding draws on the ESCO Level 3 classification system, a standardized multilingual taxonomy widely used across European labor markets. The ESCO taxonomy comprises 13,890 skills, ranging from broadly applicable soft skills such as *work in teams* to highly specialized technical competencies such as *ICT system programming* and *JavaScript*. For each job posting, Lightcast's research team assesses whether any of these skills are mentioned in the posting text.

Lightcast's ontology team, which specializes in European job postings, comprises more than 30 domain experts, including human resources specialists, labor market academics, and government officials. More than half hold doctoral degrees, and five are full-time Lightcast employees. To ensure accurate classification across languages, the team includes at least one native speaker for each language represented in the sample, including regional languages such as Catalan.

Beginning in 2017, the team developed rule-based classification dictionaries for each language, which were continuously refined through our data extraction in 2021. These dictionaries employ a detailed set of linguistic classifiers incorporating thousands of rules and keywords, including contextual neighborhood rules and negation handling. This system enables fine-grained disambiguation of semantically similar terms — for instance, distinguishing *model* as used in the context of business planning from *model* as it applies to software development.

Applying this method to our sample, the Lightcast team identifies all ESCO skills listed as requirements in each job posting. The median posting lists seven required skills, with 17 percent listing none and 47 percent listing more than ten. There is notable cross-country variation in skill listing practices: postings from Ireland, the United Kingdom, and Luxembourg list an average of more than 20 skills, whereas postings from Slovenia, Finland, Croatia, and Estonia average fewer than five.

To validate Lightcast's skill coding, we aggregate skill requirements to the occupation level and compare them against importance ratings from the Occupational Information Network (O*NET), developed by the U.S. Bureau of Labor Statistics. First published in 1998 and continuously updated since, O*NET provides standardized assessments for approximately 1,000 SOC occupations across multiple dimensions, based on representative surveys of incumbent workers supplemented by expert evaluations.

For the purposes of validation, we focus on O*NET's skill ratings, which cover 25 broad categories including skills, abilities, knowledge, and work activities. Because ESCO and O*NET employ different classification frameworks, mapping between the two systems is not always exact, and some ESCO skills may correspond to multiple O*NET categories. We manually map all ESCO skills to the most appropriate O*NET skill category, retaining only those mappings where conceptual correspondence was sufficiently clear.

Of the 25 O*NET skill categories, we identified 15 with sufficiently strong conceptual overlap with ESCO to permit meaningful cross-system comparison. These categories are: coordination, decision making, equipment maintenance, complex problem solving, programming, quality control analysis, repairing, technology design, time management, management of personnel resources, negotiation, social perceptiveness, service orientation, instructing, and

persuasion. For each category, we calculate the proportion of Lightcast job postings in each occupation that list at least one skill in that category, and compare this proportion to O*NET's importance rating for the corresponding skill dimension in the same occupation.

Appendix Figure F.2 presents the resulting correlations between Lightcast's skill coding and O*NET's importance ratings across occupations for all 15 categories. All correlations are positive and moderately strong. At the higher end, skill categories such as programming and complex problem solving yield correlations exceeding 0.45 between the proportion of Lightcast postings requiring the skill and O*NET's occupational importance rating. Even at the lower end, categories such as instructing and service orientation produce correlations above 0.30. These results provide support for the construct validity of Lightcast's skill coding. Residual discrepancies between the two systems are likely attributable to cross-country variation in job posting conventions, measurement error in both datasets, and inherent differences in classification granularity between the ESCO and O*NET frameworks.

Job Title: Front End Developer – JavaScript
Location: Remote
Company: Be-IT Resourcing
Posted: 2/19/2020
Job Type: Permanent

Description:
Fantastic opportunity for an experienced Front End Developer to join a growing software company based in Aberdeen. You will join a team building cutting-edge applications in an exciting and technically challenging environment. You should be a keen technologist looking to take a role within a team that ensures that new and cutting-edge tools/techniques are used by the software development team.

Key Skills:

- JavaScript
- Angular, Vue, React
- Experience with GIT
- Knowledge of how to layout projects and how to build large-scale web applications using AngularJS
- Commercial experience in front-end development with JavaScript and associated technologies, as well as UI implementation in HTML/CSS
- JIRA, Bitbucket
- Experience with modern browser technologies like Web Components, ESM, micro-frontends, and service workers
- Internet technologies including HTTP, and RESTful application principles and API integration (REST and RPC styles)
- End-to-end BDD-style automated acceptance tests as part of continuous delivery (Cypress, Playwright)
- Experience with Docker
- Willingness to learn new skills and attention to quality
- Comfortable in a small, fast-paced team

About the Role:

- Contributing to the design and management of the front-end application infrastructure and architecture
- Creating solutions by developing, implementing, and maintaining front-end components of web-based applications within an Agile software development environment
- Assisting with workload planning
- Assisting with the design of new software solutions
- Supporting users by developing documentation and assistance tools
- Writing tests and reviewing the work of colleagues

(a) Remote Position

Job Title: Front End Developer – JavaScript
Location: Aberdeen
Company: Be-IT Resourcing
Posted: 3/23/2021
Job Type: Permanent

Description:
Fantastic opportunity for an experienced Front End Developer to join a growing software company based in Aberdeen. You will join a team building cutting-edge applications in an exciting and technically challenging environment. You should be a keen technologist looking to take a role within a team that ensures that new and cutting-edge tools/techniques are used by the software development team.

Key Skills:

- JavaScript
- Angular
- Experience with GIT
- Knowledge of how to layout projects and how to build large-scale web applications using AngularJS
- Commercial experience in front-end development with JavaScript and associated technologies, as well as UI implementation in HTML/CSS
- Experience working with build and dependency management technologies and how these apply to / integrate with front-end development
- JIRA, Bitbucket
- Willingness to learn new skills and attention to quality
- Comfortable in a small, fast-paced team

About the Role:

- Contributing to the design and management of the front-end application infrastructure and architecture
- Creating solutions by developing, implementing, and maintaining front-end components of web-based applications within an Agile software development environment
- Assisting with workload planning
- Assisting with the design of new software solutions
- Supporting users by developing documentation and assistance tools
- Writing tests and reviewing the work of colleagues

(b) On-site Position

Figure F.1: Examples of Job Postings

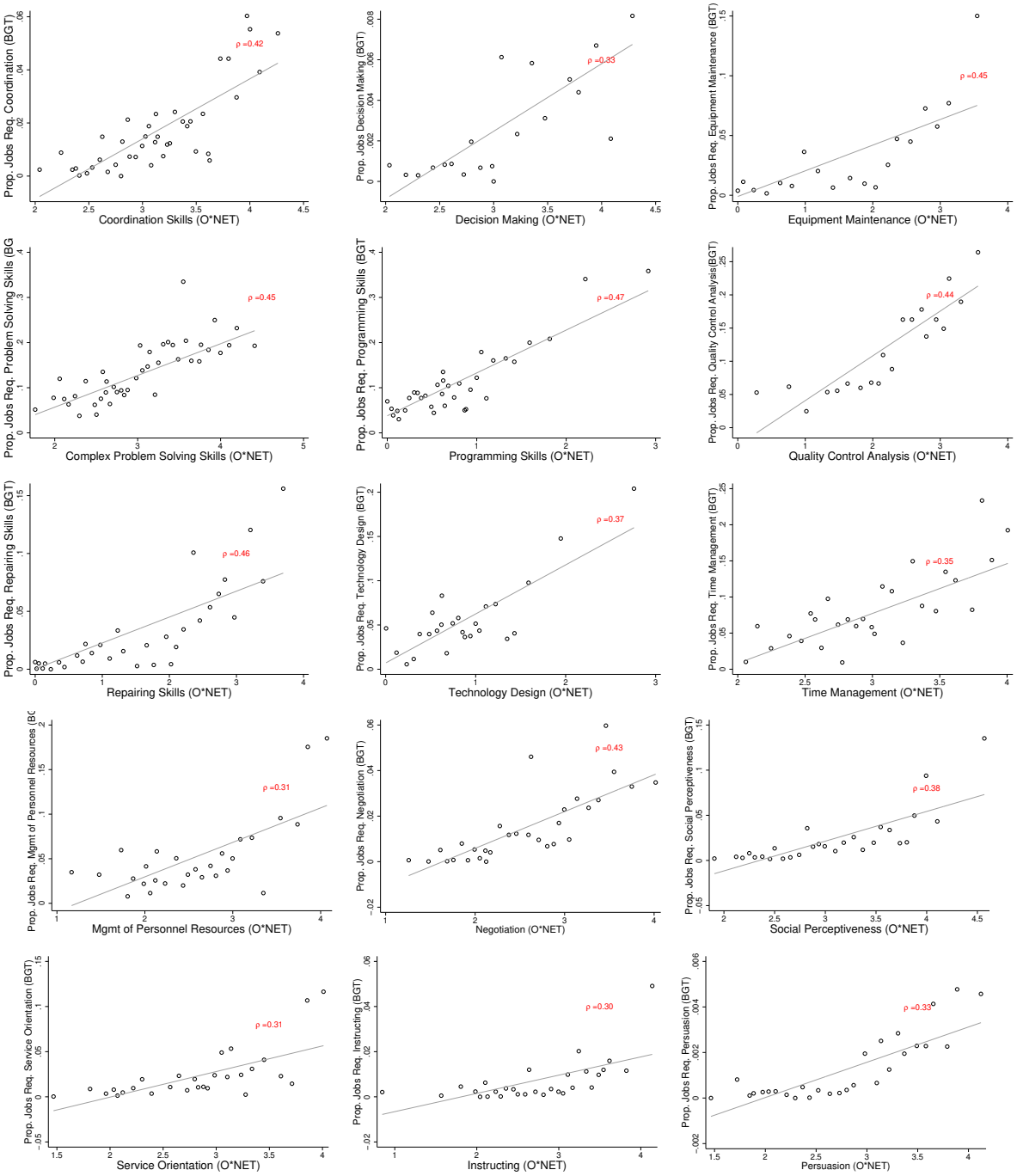


Figure F.2: Comparing Lightcast Skills and O*NET ratings

Notes: We compare the skills parsed by Lightcast to O*NET ratings at the occupation level. We use the international standard classification of occupations (ISCO), and have 440 occupations. Lightcast research team codes skills listed on each job posting. We aggregate job postings to occupation level and calculate the proportion of jobs in each occupation requiring a particular skill. We focus on 15 broad skill categories based on O*NET skill classification. We manually match Lightcast skills to one of these 15 skill categories. For each skill category, O*NET rates the importance of that skill for each of the 1000 SOC occupations based on representative occupation surveys and expert evaluation. We use Stata command *binscatter* to plot the correlation between Lightcast skill codings and O*NET's skill ratings.

Appendix Section G. Summary Statistics

Table G.1: Descriptive Statistics

	Mean	SD	Min	Max
Work Experience	1.37	2.55	0.00	10.00
Educational Level	4.42	1.37	1.00	8.00
Num. of Skills (log)	1.70	1.17	0.00	5.60
Remote Work	0.04	0.21	0.00	1.00
Social Distancing Index	27.90	33.84	0.00	96.30
Teleworkability Index	0.48	0.46	0.00	1.00
Unemployment Rate	6.14	3.10	2.01	19.29
GDP per Capita (log)	10.61	0.30	9.15	11.80

Table G.2: Pairwise Correlation

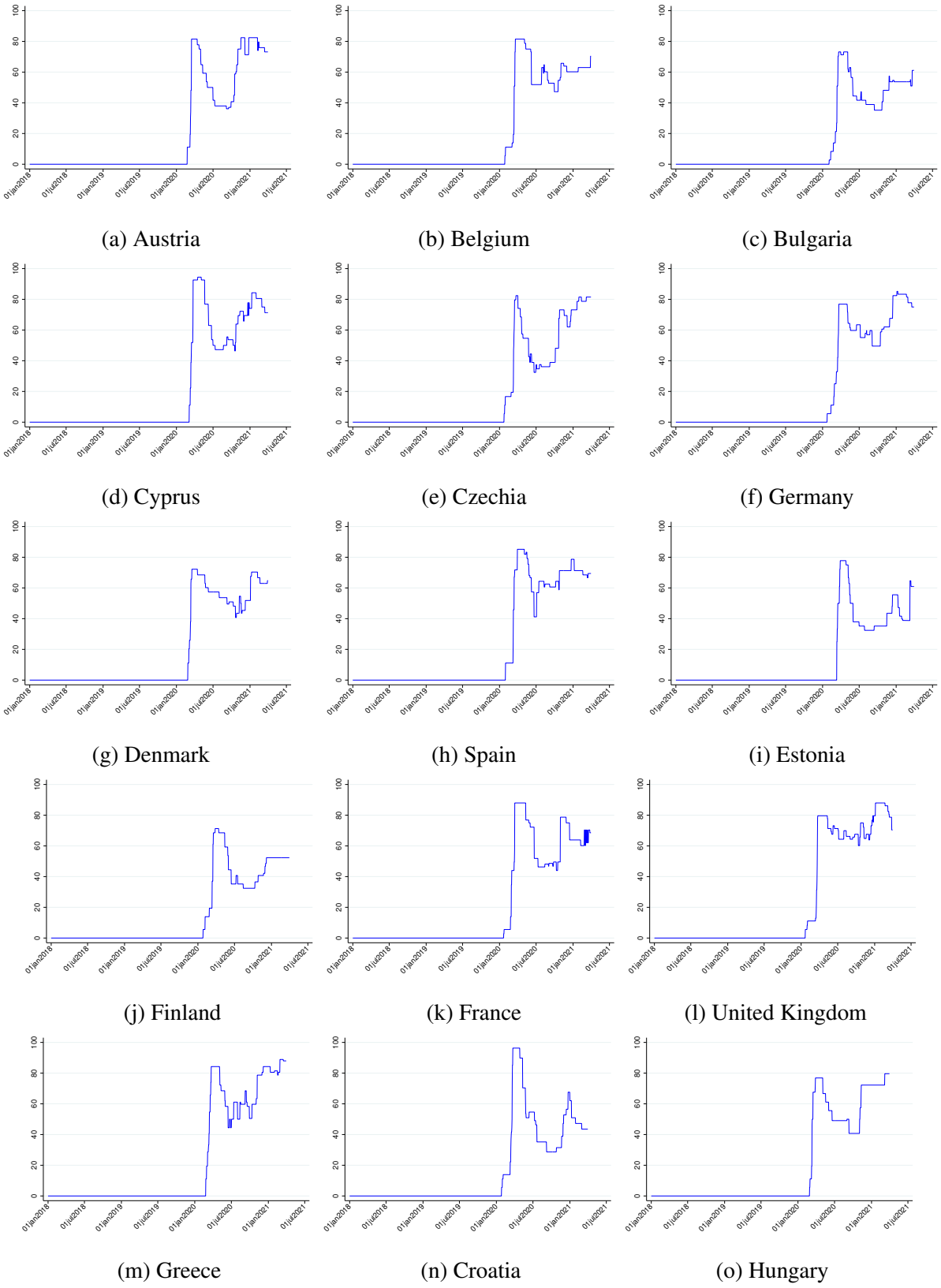
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Work Experience	1.00							
Educational Level	0.03	1.00						
Num. of Skills (log)	0.14	0.02	1.00					
Remote Work	0.03	0.02	0.16	1.00				
Social Distancing Index	0.04	-0.09	0.20	0.17	1.00			
Teleworkability Index	0.08	0.08	0.39	0.09	0.00	1.00		
Unemployment Rate	0.05	0.11	-0.12	-0.04	0.02	-0.03	1.00	
GDP per Capita (log)	-0.03	0.06	0.15	0.01	-0.00	0.02	-0.30	1.00

Appendix Section H. Stringency Index and Teleworkability Index

We use the Oxford Government Response Tracker (OxCGRT) stringency index to measure each country's social distancing regulations. Developed by Hale et al. (2021), the index is a comprehensive measure of the strictness of government lockdown-style policies that primarily restrict people's behavior. It is a composite measure based on nine key policy dimensions: school closures, workplace closures, cancellation of public events, restrictions on gathering size, closure of public transport, stay-at-home requirements, restrictions on internal movement, and restrictions on international travel. On any given day, the index is calculated as the mean score of these nine metrics, each ranging from 0 to 100. A higher score indicates a more stringent government response, with a score of 100 representing the strictest policies. The index covers over 180 countries from January 1, 2020, to December 31, 2022. Appendix Figure H.1 shows the daily fluctuations in the stringency index for each EU country. For days prior to the COVID-19 pandemic, the index is set to 0, as no social distancing regulations were in place during that period.

Appendix Figure H.2 descriptively shows a positive correlation between the stringency index of the job postings and their remote work expectations.

The teleworkability index, developed by Sostero et al. (2020), quantifies the potential for remote work across occupations. It assigns a teleworkability score to each three-digit ESCO Level 3 occupation code, ranging from 0 (indicating very limited potential for remote work) to 1 (indicating a high potential for remote work). The index is based on the physical tasks required for each occupation, with lower scores assigned to jobs that involve manual labor, on-site supervision, or the use of specialized equipment, and higher scores given to occupations that primarily involve cognitive tasks, digital tools, and independent work. A comprehensive list of teleworkability scores for all ESCO Level 3 occupations is provided in Appendix Table H.1.



(a) Austria (b) Belgium (c) Bulgaria

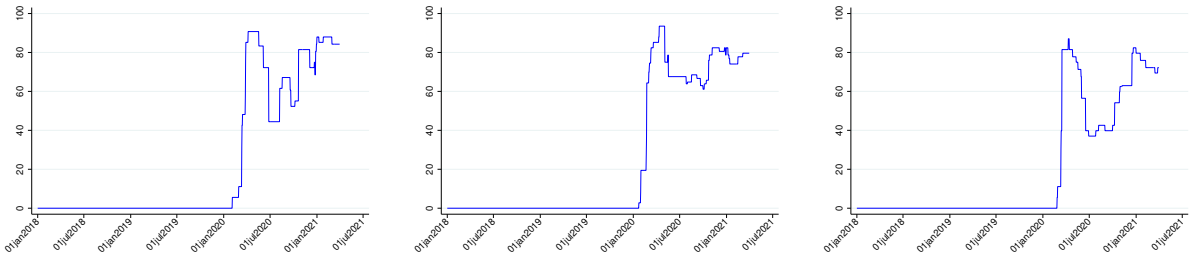
(d) Cyprus (e) Czechia (f) Germany

(g) Denmark (h) Spain (i) Estonia

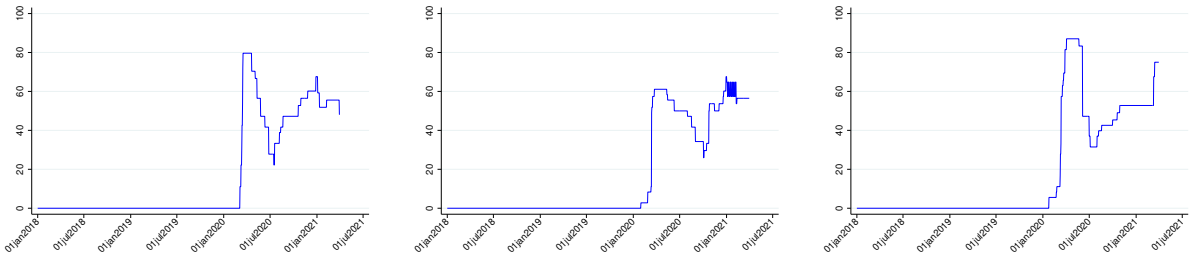
(j) Finland (k) France (l) United Kingdom

(m) Greece (n) Croatia (o) Hungary

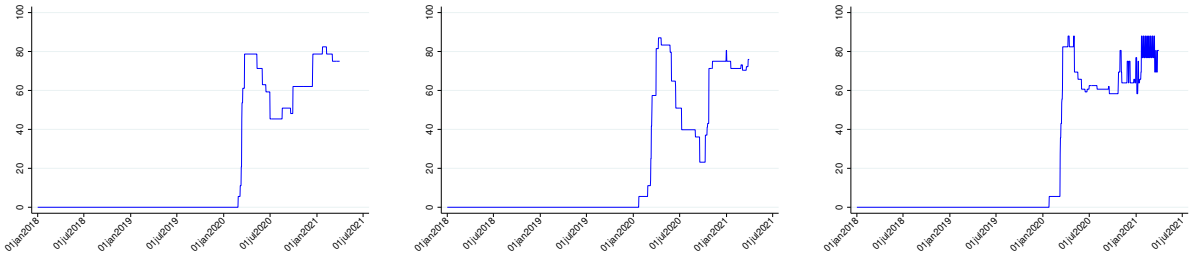
Figure H.1: Daily Stringency Index of EU Countries



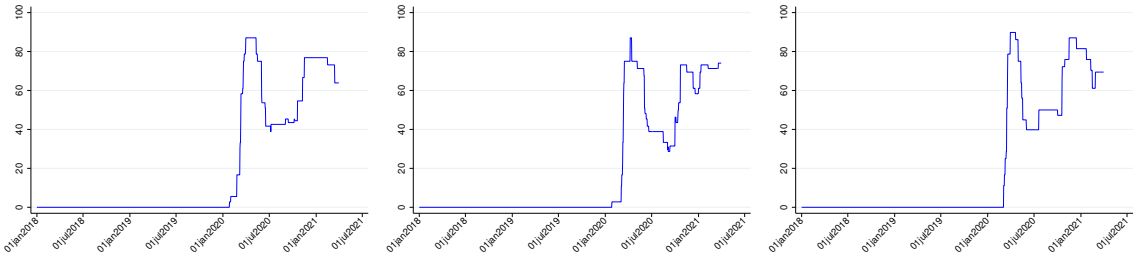
(p) Ireland (q) Italy (r) Lithuania



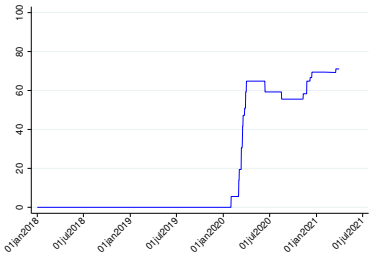
(s) Luxembourg (t) Latvia (u) Malta



(v) Netherlands (w) Poland (x) Portugal



(y) Romania (z) Slovakia () Slovenia



() Sweden

Figure H.1: Daily Stringency Index of EU Countries

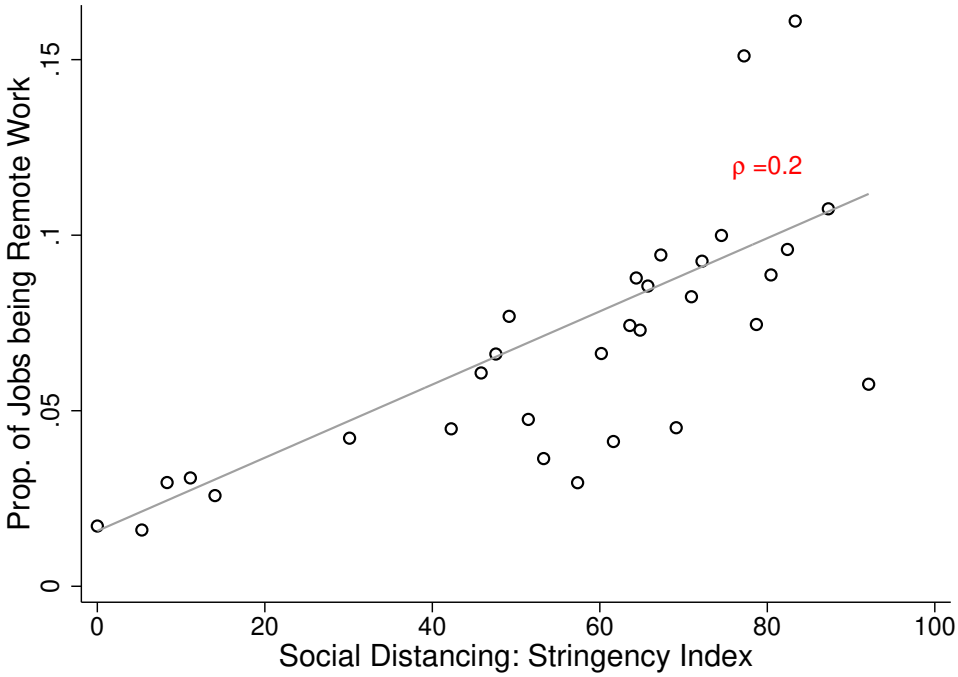


Figure H.2: Association between Social Distancing Stringency and Remote Work Expectation

Table H.1: Teleworkability Index by Occupation

ESCO Level3 ID	ESCO Level 3 Occupation	Teleworkability Index
111	Legislators and senior officials	1.000
112	Managing directors and chief executives	1.000
121	Business services and administration managers	1.000
122	Sales, marketing and development managers	1.000
131	Production managers in agriculture, forestry and fisheries	0.000
132	Manufacturing, mining, construction, and distribution managers	0.179
133	Information and communications technology service managers	1.000
134	Professional services managers	1.000
141	Hotel and restaurant managers	0.970
142	Retail and wholesale trade managers	0.067
143	Other services managers	0.887
211	Physical and earth science professionals	0.232
212	Mathematicians, actuaries and statisticians	1.000
213	Life science professionals	0.260
214	Engineering professionals (excluding electrotechnology)	0.250
215	Electrotechnology engineers	0.000
216	Architects, planners, surveyors and designers	0.376
221	Medical doctors	0.392
222	Nursing and midwifery professionals	0.000
225	Veterinarians	0.000
226	Other health professionals	0.587
231	University and higher education teachers	0.495
232	Vocational education teachers	1.000
233	Secondary education teachers	1.000
234	Primary school and early childhood teachers	0.612
235	Other teaching professionals	0.860
241	Finance professionals	1.000
242	Administration professionals	0.971
243	Sales, marketing and public relations professionals	1.000
251	Software and applications developers and analysts	1.000
252	Database and network professionals	1.000
261	Legal professionals	1.000
262	Librarians, archivists and curators	1.000
263	Social and religious professionals	0.977
264	Authors, journalists and linguists	1.000
265	Creative and performing artists	0.339
311	Physical and engineering science technicians	0.007
312	Mining, manufacturing and construction supervisors	0.000
313	Process control technicians	0.019
314	Life science technicians and related associate professionals	0.630
315	Ship and aircraft controllers and technicians	0.091
321	Medical and pharmaceutical technicians	0.000
322	Nursing and midwifery associate professionals	0.000
324	Veterinary technicians and assistants	0.000
325	Other health associate professionals	0.347
331	Financial and mathematical associate professionals	0.997
332	Sales and purchasing agents and brokers	1.000
333	Business services agents	1.000
334	Administrative and specialised secretaries	1.000
335	Regulatory government associate professionals	0.526
341	Legal, social and religious associate professionals	1.000
342	Sports and fitness workers	0.044
343	Artistic, cultural and culinary associate professionals	0.110
351	Information and communications technology operations and user support technicians	0.934
352	Telecommunications and broadcasting technicians	0.000
411	General office clerks	1.000
412	Secretaries (general)	1.000
413	Keyboard operators	1.000
421	Tellers, money collectors and related clerks	0.929
422	Client information workers	1.000
431	Numerical clerks	1.000

Continued on next page

Table H.1 – *Continued from previous page*

432	Material-recording and transport clerks	0.399
441	Other clerical support workers	0.819
511	Travel attendants, conductors and guides	0.730
512	Cooks	0.000
513	Waiters and bartenders	0.000
514	Hairdressers, beauticians and related workers	0.000
515	Building and housekeeping supervisors	0.000
516	Other personal services workers	0.324
521	Street and market salespersons	0.000
522	Shop salespersons	0.042
523	Cashiers and ticket clerks	0.101
524	Other sales workers	0.327
531	Child care workers and teachersâÃÃ´ aides	0.000
532	Personal care workers in health services	0.000
541	Protective services workers	0.396
611	Market gardeners and crop growers	0.000
612	Animal producers	0.000
613	Mixed crop and animal producers	0.000
621	Forestry and related workers	0.000
622	Fishery workers, hunters and trappers	0.000
711	Building frame and related trades workers	0.000
712	Building finishers and related trades workers	0.000
713	Painters, building structure cleaners and related trades workers	0.000
721	Sheet and structural metal workers, moulders and welders, and related workers	0.000
722	Blacksmiths, toolmakers and related trades workers	0.000
723	Machinery mechanics and repairers	0.000
731	Handicraft workers	0.000
732	Printing trades workers	0.335
741	Electrical equipment installers and repairers	0.000
742	Electronics and telecommunications installers and repairers	0.000
751	Food processing and related trades workers	0.003
752	Wood treaters, cabinet-makers and related trades workers	0.000
753	Garment and related trades workers	0.000
754	Other craft and related workers	0.000
811	Mining and mineral processing plant operators	0.000
812	Metal processing and finishing plant operators	0.000
813	Chemical and photographic products plant and machine operators	0.000
814	Rubber, plastic and paper products machine operators	0.000
815	Textile, fur and leather products machine operators	0.252
816	Food and related products machine operators	0.000
817	Wood processing and papermaking plant operators	0.000
818	Other stationary plant and machine operators	0.000
821	Assemblers	0.000
831	Locomotive engine drivers and related workers	0.000
832	Car, van and motorcycle drivers	0.000
833	Heavy truck and bus drivers	0.000
834	Mobile plant operators	0.000
835	Ships' deck crews and related workers	0.000
911	Domestic, hotel and office cleaners and helpers	0.000
912	Vehicle, window, laundry and other hand cleaning workers	0.000
921	Agricultural, forestry and fishery labourers	0.000
931	Mining and construction labourers	0.000
932	Manufacturing labourers	0.000
933	Transport and storage labourers	0.000
941	Food preparation assistants	0.000
951	Street and related service workers	0.000
952	Street vendors (excluding food)	0.000
961	Refuse workers	0.000
962	Other elementary workers	0.283

Notes: This table lists the teleworkability index calculated by Sostero et al. (2020). Each 3-digit occupational code (ESCO level 3) was assigned a teleworkability score ranging from 0 (fully non-teleworkable) to 1 (fully teleworkable).

Appendix Section I. Additional Robustness Checks

This section presents additional analyses to validate the robustness of our main findings. We examine the sensitivity of our results to alternative fixed effect specifications, sample restrictions, and variable definitions.

Appendix Section I.1. Job Title and Job Task Fixed Effects

One potential concern is that remote and in-person positions may differ systematically in their tasks and responsibilities. While occupation fixed effects help address this issue, a single occupation can encompass many distinct jobs with varying task characteristics. To provide a more granular comparison, we estimate models using job title fixed effects in place of occupation fixed effects. With approximately 21 million unique job titles compared to 352 ESCO occupations, this specification ensures that we compare highly similar roles, as tasks and responsibilities vary much less within the same job title and employer. As shown in Appendix Table I.1, the estimated effects remain largely unchanged, suggesting that broader occupation groupings do not meaningfully obscure the relationship of interest.

We also incorporate task combinations as fixed effects. Some ESCO skills — such as *develop statistical software* and *inspect construction sites* — reflect tasks performed on the job rather than qualifications held by the worker. We manually identify all such task-like ESCO skills and use their dyadic combinations as fixed effects. For example, a job listing tasks A, B, and C is assigned the combination A-B-C and compared only to other jobs with the identical combination. Appendix Table I.2 reports results using occupation-task-country-employer fixed effects, where the task variable captures the full combination of tasks listed in each posting. This stricter specification yields substantively similar findings.

Appendix Section I.2. Regional Fixed Effects

For multi-establishment employers, firm-level fixed effects may mask variation across establishments. Some firms may assign certain subsidiaries exclusively to remote work while keeping others fully in-person, which could introduce unobserved confounders related to location-specific factors. To address this concern, we estimate models with fixed effects at the employer-region-occupation level, where region is measured at the NUTS-1 level — a finer geographic unit than the country-level fixed effects used in our main specification. As shown in Appendix Table I.3, results from this specification remain consistent with our main findings.

Appendix Section I.3. Pre-COVID Sample

Approximately half of our observations fall within the COVID-19 pandemic period, which was marked by significant social, economic, and labor market disruptions. To ensure that our findings are not driven by unobserved pandemic-era dynamics, we replicate our main analyses using only the pre-pandemic sample. As shown in Appendix Table I.4, the results are highly consistent with those from the full sample, suggesting that our main findings are not an artifact of the pandemic period.

Appendix Section I.4. Hybrid Work

Our main analyses focus on fully remote positions. To assess whether hybrid work exhibits similar patterns, we examine hybrid job postings 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. As shown in Appendix Table I.5, the skill requirements of hybrid jobs closely resemble those of in-person roles, consistent with our argument that hybrid

work functions more like in-person than fully remote work. Given the small sample size, however, these results should be interpreted with caution.

Appendix Section I.5. Controlling for Job Posting Length

A potential alternative explanation for our findings is that remote job postings are simply longer, mechanically increasing the number of listed skills. To address this concern, Appendix Table I.6 replicates our main models while controlling for the log length of each job posting. The results remain substantively unchanged, suggesting that posting length does not account for the elevated skill requirements observed in remote positions.

Table I.1: Linear Estimation of Hiring Requirements: Including Title Fixed Effect

	Num. of Skills (log)		Work Experience				Educational Level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote Work	0.259***	0.260***	0.0810***	0.0716***	0.0467**	0.0258*	0.0254***	0.0371***	0.0247***	0.0304***
	(0.0118)	(0.0127)	(0.0151)	(0.0126)	(0.0157)	(0.0122)	(0.00686)	(0.00891)	(0.00698)	(0.00912)
Num. of Skills (log)					0.132***	0.176***			0.00263	0.0260***
					(0.00924)	(0.0108)			(0.00549)	(0.00427)
Observations	51872468	51872468	51872468	51872468	51872468	51872468	51446418	51446418	51446418	51446418
R^2	0.855	0.877	0.594	0.663	0.594	0.664	0.798	0.833	0.798	0.833
Fixed Effects:										
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job Title x Country	Yes		Yes		Yes		Yes		Yes	
Job Title x Employer x Country		Yes		Yes		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table I.2: Linear Estimation of Hiring Requirements: Including Task Fixed Effect

	Num. of Skills (log)		Work Experience				Educational Level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote Work	0.135***	0.124***	0.206***	0.135***	0.175***	0.121***	0.0568***	0.0543*	0.0492**	0.0502*
	(0.00357)	(0.00493)	(0.0104)	(0.0216)	(0.0102)	(0.0215)	(0.0169)	(0.0224)	(0.0165)	(0.0222)
Non-task Skills (log)					0.218***	0.137***			0.0534***	0.0390***
					(0.00738)	(0.0120)			(0.00517)	(0.00490)
Observations	44351211	27729750	44351211	27729750	44351211	27729750	44001162	27450197	44001162	27450197
R^2	0.813	0.879	0.269	0.548	0.270	0.548	0.453	0.678	0.454	0.678
Fixed Effects:										
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job Task x Occupation x Country	Yes		Yes		Yes		Yes		Yes	
Job Task x Occupation x Employer x Country		Yes		Yes		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table I.3: Linear Estimation of Hiring Requirements: Including Region Fixed Effect

	Num. of Skills (log)		Work Experience				Educational Level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote Work	0.376***	0.293***	0.185***	0.0909***	0.111***	0.0409**	0.0961***	0.0717**	0.0773***	0.0567*
	(0.00946)	(0.0117)	(0.0108)	(0.0149)	(0.0110)	(0.0138)	(0.0217)	(0.0245)	(0.0209)	(0.0241)
Num. of Skills (log)					0.198***	0.171***			0.0500***	0.0512***
					(0.00567)	(0.00761)			(0.00468)	(0.00420)
Observations	39361249	30595040	39361249	30595040	39361249	30595040	39044943	30318440	39044943	30318440
R^2	0.574	0.781	0.068	0.407	0.071	0.409	0.299	0.575	0.300	0.576
Fixed Effects:										
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Country x Region	Yes		Yes		Yes		Yes		Yes	
Occupation x Employer x Country x Region		Yes		Yes		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table I.4: Linear Estimation of Hiring Requirements: Pre-Covid Period

	Num. of Skills (log)		Work Experience				Educational Level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote Work	0.472***	0.261***	0.292***	0.147***	0.172***	0.0922**	0.168*	0.137***	0.142*	0.123***
	(0.0149)	(0.00780)	(0.0205)	(0.0298)	(0.0191)	(0.0296)	(0.0699)	(0.0313)	(0.0686)	(0.0309)
Num. of Skills (log)					0.254***	0.209***			0.0559***	0.0535***
					(0.00716)	(0.00959)			(0.00540)	(0.00579)
Observations	27246864	22080792	27246864	22080792	27246864	22080792	26929692	21798863	26929692	21798863
R^2	0.526	0.752	0.066	0.357	0.072	0.360	0.266	0.533	0.267	0.534
Fixed Effects:										
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Country	Yes		Yes		Yes		Yes		Yes	
Occupation x Employer x Country		Yes		Yes		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table I.5: Linear Estimation of Skill Requirements: Testing Mechanisms for Remote and Hybrid Work

	Num. of Skills (log)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote Work x On-the-job Training			0.0239***	0.0425***						
			(0.00407)	(0.00460)						
Hybrid Work x On-the-job Training			0.00516	0.0123						
			(0.0151)	(0.0147)						
Remote Work x Importance of Independence					-0.0481***	-0.0619***				
					(0.00940)	(0.0115)				
Hybrid Work x Importance of Independence					0.0212	-0.0340				
					(0.0536)	(0.0528)				
Remote Work x Hard-to-fill Jobs							0.198***	0.227***		
							(0.0157)	(0.0125)		
Hybrid x Hard-to-fill Jobs							0.0435	-0.00911		
							(0.0309)	(0.0227)		
Remote Work x Unemployment Rate									-0.0131***	-0.0194***
									(0.00222)	(0.00248)
Hybrid Work x Unemployment Rate									0.00566	-0.00380
									(0.00801)	(0.00746)
Remote Work	0.360***	0.248***	0.318***	0.175***	0.559***	0.511***	-0.454***	-0.704***	0.431***	0.349***
	(0.00859)	(0.00897)	(0.00941)	(0.00917)	(0.0399)	(0.0446)	(0.0665)	(0.0486)	(0.0145)	(0.0175)
Hybrid Work	0.161***	0.0592***	0.158***	0.0441	0.0725	0.177	-0.0332	0.113	0.132**	0.0757*
	(0.0231)	(0.0139)	(0.0325)	(0.0236)	(0.205)	(0.207)	(0.133)	(0.0886)	(0.0448)	(0.0374)
Unemployment Rate (Combined)									0.00700***	0.00293**
									(0.00140)	(0.00110)
Observations	51751672	43139329	50632849	42176569	44559101	36886808	41321194	36273599	51751672	43139329
R^2	0.588	0.781	0.589	0.782	0.568	0.770	0.578	0.763	0.588	0.781
Fixed Effects:										
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Country	Yes		Yes		Yes		Yes		Yes	
Occupation x Employer x Country		Yes		Yes		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table I.6: Linear Estimation of Hiring Requirements: Controlling for Job Posting Length

	Num. of Skills (log)		Work Experience		Educational Level	
	(1)	(2)	(3)	(4)	(5)	(6)
Remote Work	0.161***	0.127***	0.160***	0.0620***	0.0863***	0.0633***
	(0.00935)	(0.00721)	(0.0134)	(0.0113)	(0.0189)	(0.0185)
Job Posting Length (log)	0.494***	0.494***	0.194***	0.237***	0.00402	0.0200***
	(0.00538)	(0.00517)	(0.00974)	(0.0107)	(0.00757)	(0.00606)
Observations	49935418	41548096	49935418	41548096	49515056	41169327
R^2	0.705	0.828	0.062	0.349	0.300	0.546
Fixed Effects:						
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Country	Yes		Yes		Yes	
Occupation x Employer x Country		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Section J. Definition of On-the-Job Training

The Bureau of Labor Statistics (BLS) defines **On-the-Job Training (OJT)** as the minimum time workers need after hiring to acquire the skills and knowledge necessary for effective job performance.

OJT Includes:

- Time workers take to learn basic job tasks while being actively taught by a supervisor or a more experienced worker.
- On-the-job training with verbal and written instruction, demonstration and observation, hands-on practice, or imitation.
- Vocationally relevant classes or training needed to do the job, including in-plant or internal company training.
- Time spent shadowing.

OJT Excludes:

- Continuing education.
- Time spent learning tasks that are beyond the basic requirements of the job.
- Orientation on topics such as company policies, workplace rules, or company benefits.
- Time during the probationary period that does not overlap active training.
- Coaching for job development.

To create the OJT measure, the BLS uses data from the *Occupational Requirements Survey (ORS)*, a nationally representative establishment-based survey. The survey gathers information from a probability sample of 56,300 establishments. This sample includes 25,100 private industry establishments and 5,000 state and local government respondents, resulting in approximately 148,600 occupational observations. The 2023 estimates represent 145,866,200 civilian workers and aggregate five annual samples collected between September 2018 and July 2023. These data form the final estimates for the second wave of the ORS, providing a robust representation of the civilian workforce.

At the occupation level, the BLS measures OJT by capturing the minimum training time required, using the lower bound of reported durations and aggregating data to produce national estimates. The measure includes only vocationally relevant training, such as shadowing experienced workers or receiving direct instruction on job tasks. When respondents cannot specify exact estimates, fallback coding techniques refine the data. For instance, training described as less than a week is coded as 0.9 weeks. The BLS also uses threshold-based questions, such as “Is OJT more than a month?” or “Is OJT more than a year?” to narrow the range. Probationary periods are excluded unless they overlap with active training.

Appendix Section K. Descriptive Patterns in Models

Our identification strategy relies on fixed effects models that compare jobs within the same occupation, posted by the same employer, in the same country and year. A natural concern with this approach is whether sufficient within-group variation in remote work status exists to identify the effect of interest. Appendix Table K.1 addresses this concern by reporting the number of fixed effect groups and the proportion exhibiting variation in remote work status under each model specification. Under the occupation-country fixed effects specification, 65 percent of groups contain both remote and non-remote postings. Introducing firm-level fixed effects reduces this proportion to 9 percent, reflecting the concentration of remote work within a subset of firms. Under our strictest specification — firm-title-country fixed effects (Appendix Table I.1) — the proportion falls further to 3.4 percent. Nevertheless, this specification yields 6,637,570 non-singleton fixed effect groups, providing sufficient statistical power to identify the effects of interest.

We also characterize the types of firms that are more likely to post both remote and non-remote positions within the same year, as these firms constitute the primary source of identifying variation in our strictest models. Appendix Table K.2 reports descriptive statistics separately for all firms, firms that posted both remote and non-remote jobs at any point in our sample, and firms that did so within the same calendar year. Several patterns emerge. First, firms that post both types of positions tend to be substantially larger, as measured by total job postings. Second, these firms also have greater prior exposure to remote work, with an average of approximately 10 percent of their pre-COVID postings classified as remote, compared to 1.2 percent among all firms in the sample. Third, while manufacturing is the most common industry in the overall sample, the administrative and support services sector is disproportionately represented among firms posting both remote and non-remote positions. Importantly, as shown in Appendix Table L.3, interacting remote work with firm size and prior remote work experience does not yield consistent evidence that these firm characteristics moderate the main relationship, suggesting that the elevated skill requirements associated with remote work are not primarily driven by the specific subset of firms that account for most of the identifying variation.

Table K.1: Descriptive Patterns in Fixed Effects Models

	Num. of Non-singleton FE Groups	Avg. Num. of Postings per Group	Prop. Groups with Variations in Remote Work Status
Occupation FE	424	122340.7	99.3%
Occupation-Country FE	10,987	4721.2	64.9%
Firm-Occupation-Country FE	5,029,129	8.8	9.0%
Firm-Occupation-Country-Year FE	5,616,937	7.5	8.0%
Firm-Title-Country FE	6,637,570	3.5	3.4%

Notes: We exclude singleton observations within each fixed effect groups.

Table K.2: Descriptive Patterns in Firms

	All firms	Firms posted remote and non-remote jobs	Firms posted remote and non-remote jobs in the same year
Num. of Firms	3,575,957	239,748	213,855
Avg. num of Job Postings	15	141	157
Prop. of Remote Jobs before Covid	1.2%	9.5%	9.2%
Prop. of Remote Jobs	5.9%	29.2%	27.2%
Most Common Industry	Manufacturing	Administrative and support service activities	Administrative and support service activities

Appendix Section L. Potential Mechanisms

Appendix Section L.1. On-the-Job Training and Support

Remote jobs requiring extensive on-the-job training (OJT) face greater challenges in skill development, as the difficulty of providing real-time guidance and hands-on instruction at a distance may compel employers to seek candidates who already possess the necessary skills. Consistent with this reasoning, Appendix Table L.1 shows that the positive association between remote work and skill expectations is stronger for occupations that require more OJT and weaker for those that require less.

A related concern is the difficulty of providing on-the-job support in highly interdependent roles. In such settings, workers frequently rely on colleagues for guidance, feedback, and problem-solving assistance — resources that are harder to access in remote environments. Using O*NET job independence scores as a measure of interdependence, Appendix Table L.1 shows that the positive association between remote work and skill requirements is more pronounced in low-independence occupations and attenuates in occupations where workers operate more autonomously.

Appendix Section L.2. Unemployment Rate and Hard-to-Fill Jobs

The size of the applicant pool also shapes how employers set skill requirements for remote positions. When the pool of available workers is relatively constrained — for instance, during periods of low unemployment or for positions that are traditionally difficult to fill — employers face greater uncertainty about attracting suitable candidates and may therefore specify more demanding qualifications upfront. Conversely, when unemployment is higher or positions are easier to fill, employers may have less need to front-load skill demands, as an adequate supply of qualified candidates is more readily available.

Consistent with this reasoning, Appendix Table L.1 shows that remote jobs are associated with higher skill requirements in regions with lower unemployment rates and for positions that are harder to fill. We operationalize job difficulty using Lightcast's estimate of the number of days a posting remains active before being taken down, aggregated to the occupation–firm level using pre-2020 data to ensure that the measure reflects baseline fill durations unaffected by the rise of remote work during the pandemic. Positions with longer average durations are therefore treated as harder to fill. Together, these patterns suggest that the impact of remote work on hiring standards is particularly pronounced when recruiting conditions are more constrained and the value of an expanded applicant pool is greatest.

Appendix Section L.3. Generalized Trust

A third potential mechanism is that remote work, by making it harder to observe worker effort and build interpersonal trust, leads employers to rely more heavily on verifiable qualifications when evaluating candidates. If this mechanism is operative, we would expect the remote work premium in skill requirements to be larger in lower-trust environments, where monitoring difficulties are more severe. Consistent with this prediction, Appendix Table L.1 shows that the association between remote work and skill requirements is somewhat stronger in lower-trust countries, though as discussed in the main text, the overall evidence for this mechanism is mixed.

Appendix Section L.4. Emphasis on Measurable Skills

A related possibility is that remote work shifts employer preferences toward skills that are more easily observable and verifiable — such as technical certifications or quantifiable competencies — relative to more intangible attributes like cultural fit or interpersonal style. To assess this, we used GPT-4 to rate each ESCO skill on a measurability scale from 1 to 5, where higher scores indicate skills that are more concrete, clearly defined, and directly assessable in standard hiring contexts (e.g., through resumes, interviews, tests, portfolios, or references). Each skill was rated using the following prompt:

> *You are evaluating how easily a skill can be measured in standard hiring contexts. Each skill is part of the ESCO taxonomy and was extracted from employer job postings. Evaluate measurability: how easily the skill can be observed or assessed in recruitment processes (resumes, interviews, tests, portfolios, or references). The focus is exclusively on the ease of defining concrete, observable, or testable criteria for assessment in hiring. Rate on a 1–5 scale, where 1 indicates a highly abstract or general skill that is extremely difficult to assess objectively, and 5 indicates a highly specific, clearly defined skill that is directly tied to measurable outputs or qualifications.*

We then compute the average measurability score across all skills listed in each job posting. As shown in Appendix Table L.2, we do not find evidence of a systematic shift toward more easily measurable skills in remote job postings, providing limited support for this mechanism.

Appendix Section L.5. Firm Characteristics

Finally, we examine whether firm-level characteristics moderate the relationship between remote work and skill requirements. Firms with greater prior experience in remote work may have developed the organizational infrastructure and managerial practices needed to support remote employees effectively, potentially reducing the need to hire workers with higher upfront qualifications. Using the proportion of remote job postings within a firm prior to COVID-19 as a proxy for remote work experience, Appendix Table L.3 provides suggestive but mixed evidence on this relationship, with no consistent pattern emerging across specifications.

We also examine firm size as a potential moderator, on the grounds that larger firms may be better positioned to invest in remote work infrastructure and training programs. However, Appendix Table L.3 does not reveal a clear or consistent moderating effect of firm size, suggesting that the elevated skill requirements associated with remote work are not substantially attenuated in larger organizations.

Table L.1: Linear Estimation of Skill Requirement: Mechanisms

	On-the-job Training		On-the-job Support		Hard-to-fill Jobs		Unemployment Rate		Generalized Trust	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Remote Work x On-the-job Training	0.0239***	0.0425***								
	(0.00407)	(0.00460)								
Remote Work x Importance of Independence			-0.0480***	-0.0619***						
			(0.00940)	(0.0115)						
Remote Work x Hard-to-fill Jobs					0.222***	0.227***				
					(0.0205)	(0.0125)				
Remote Work x Unemployment Rate							-0.0131***	-0.0194***		
							(0.00222)	(0.00248)		
Remote Work x Social Trust									-0.449***	-0.107*
									(0.0699)	(0.0527)
Remote Work	0.318***	0.175***	0.559***	0.511***	-0.559***	-0.704***	0.431***	0.349***	0.518***	0.287***
	(0.00941)	(0.00917)	(0.0398)	(0.0446)	(0.0914)	(0.0486)	(0.0145)	(0.0175)	(0.0246)	(0.0183)
Hard-to-fill Jobs					-0.0431					
					(0.0275)					
Unemployment Rate (Combined)							0.00700***	0.00293**		
							(0.00140)	(0.00110)		
Observations	50632849	42176569	44559101	36886808	41321194	36273599	51751672	43139329	51751672	43139329
R^2	0.589	0.782	0.568	0.770	0.578	0.763	0.588	0.781	0.588	0.781
Fixed Effects:										
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Country	Yes		Yes		Yes		Yes		Yes	
Occupation x Employer x Country		Yes		Yes		Yes		Yes		Yes
Job Portal		Yes		Yes		Yes		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table L.2: Linear Estimation of Skill Measurability

	Skill Measurability (GPT)			
	(1)	(2)	(3)	(4)
Remote Work	0.00447	0.0307***	-0.0101***	0.0165***
	(0.00280)	(0.00249)	(0.00245)	(0.00225)
Num. of Skills (log)			0.0483***	0.0654***
			(0.00256)	(0.00369)
Observations	45262022	37984025	45262022	37984025
R^2	0.292	0.564	0.296	0.569
Fixed Effects:				
Posting Year	Yes	Yes	Yes	Yes
Occupation x Country	Yes		Yes	
Occupation x Employer x Country		Yes		Yes
Job Portal		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table L.3: Linear Estimation of Skill Requirements: The Moderating Effect of Company Characteristics

	Prop. of Remote Work in Company		Employer Size (log)	
	(1)	(2)	(3)	(4)
Remote Work x Prop. of Remote Work	-0.925***	0.184***		
	(0.183)	(0.0514)		
Remote Work x Employer Size (log)			-0.00481	0.00796**
			(0.00313)	(0.00265)
Remote Work	0.392***	0.251***	0.398***	0.196***
	(0.0165)	(0.0111)	(0.0138)	(0.0114)
Prop. of Remote Work	1.087***			
	(0.159)			
Employer Size (log)			0.0226***	0.0424***
			(0.00580)	(0.00421)
Observations	46224367	39823377	51751672	43139329
R^2	0.584	0.771	0.591	0.781
Fixed Effects:				
Posting Year	Yes	Yes	Yes	Yes
Occupation x Country	Yes		Yes	
Occupation x Employer x Country		Yes		Yes
Job Portal		Yes		Yes

Standard errors clustered at the firm level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Section M. Experimental Design

This section provides additional detail on the design and implementation of our online experiment. The experiment employed a $2 \times 3 \times 3$ factorial design, varying work setting (remote vs. in-person), qualification dimension (skills, work experience, or education level), and job role (data scientist, marketing analyst, or sales representative). This design yields 18 distinct experimental conditions, allowing us to examine how remote work influences hiring expectations across different job functions and qualification dimensions. Appendix Figure M.1 illustrates the experimental materials for one representative condition — a remote data scientist role in which participants were asked to specify work experience requirements. All other conditions followed an identical structure with the appropriate substitutions.

As described in the main text, the survey included several attention-check questions to screen for inattentive responding. After applying all exclusion criteria, 1,250 valid responses were retained for analysis. Appendix Table M.1 reports the demographic characteristics of the analytical sample.

To shed further light on the mechanisms underlying participants' hiring decisions, we analyzed their open-ended responses explaining the rationale for their qualification choices. Because participants were not informed that the study concerned remote work, many provided rationales unrelated to work arrangement. In other cases, participants attributed their choices to the remote nature of the position without specifying a mechanism. The following response is representative of this pattern:

> "I think that a couple of years of experience is enough especially if you hire someone to work on site. For remote work I would say more."

Two research associates, blind to the study hypotheses, independently coded each open-ended response. They identified responses that explicitly referenced working arrangements and categorized them according to the mechanism invoked. Disagreements were resolved through discussion with the authors. Of the 1,250 responses, 344 (27.5 percent) explicitly articulated a mechanism linking work arrangement to hiring requirements. Appendix Table M.2 summarizes the distribution of mechanisms across experimental conditions.

The most frequently cited mechanism was the difficulty of providing training and on-the-job support in remote settings, mentioned by 186 participants (54.1 percent of those who articulated a mechanism). The following responses are illustrative:

> "I feel for remote workers it is understandable that a greater amount of experience is required. Firstly this will generally mean a slightly older and more mature candidate, and it also means that little to no training will be required - which i find to be difficult for remote workers."

> "As this is an onsite position, training will be able to be delivered effectively and therefore I feel that they would only need the most essential skills, the rest can be taught."

Several participants also emphasized the difficulty of providing informal mentorship and supervisory support in remote environments:

> "As they can work anywhere, monitoring them daily could be difficult, so I would want them to be experienced and be able to work without supervision."

> "Working on-site should be able to shadow experienced staff and be closely mentored."

The second most commonly cited mechanism — and one central to our theoretical argument — was the expansion of the applicant pool enabled by remote work. Twenty-eight participants (8.1 percent) noted that the geographic reach of remote positions attracts a substantially larger pool of applicants, allowing employers to set more demanding qualifications. Representative responses include:

> "I do not see why I would not require most of the skills, since the position is available for application anywhere in the world. There will be no shortage of skilled applicants."

> "I think it is reasonable to expect the candidate to meet the requirement of having all relevant skills for the position. This is particularly relevant if the position is remote, as the potential pool of candidates is significant. If there are any issues with sourcing a suitable candidate, the requirements of the role could always be scaled back to 'most relevant' skills."

Additional mechanisms cited by participants include concerns about trust and commitment (23 participants, 6.7 percent), the need for self-motivation and initiative (18 participants, 5.2 percent), and challenges related to collaboration and organizational culture (14 participants, 4.1 percent).

Taken together, the qualitative responses corroborate the quantitative findings reported in the main text. Participants most frequently attributed higher hiring requirements for remote positions to the challenges of providing training and support at a distance, followed by the expanded applicant pool that remote work affords. The recurrence of themes related to self-direction, accountability, and collaboration further suggests that participants perceive remote roles as demanding greater autonomy and prior expertise — consistent with the mechanisms proposed in our theoretical framework.

Start of Block: ID

Q1 Please enter your Prolific ID:

_____

End of Block: ID

Start of Block: Intro

What you will do in this experiment: In this study, you will help to draft job descriptions for a position.

Time required:
The session will take approximately 4 minutes to complete.

Confidentiality:
Your participation in this study will remain confidential, and your identity will not be stored with your data.

Potential risks and benefits:
The risks are no more than what you would encounter in everyday life.

Payment for participation:
For successfully completing the survey you will be rewarded with the incentive listed in the invite you received to participate in this study.

End of Block: Intro

Start of Block: intro2

We are [redacted], a startup specializing in semiconductor manufacturing. We have struggled to hire successful candidates and would love to learn about your insights into recruitment.

End of Block: intro2

Start of Block: attention

Before we get started, we want to learn a bit about your work experiences on hiring and recruitment.

Q1 How many years of hiring experience do you have so far?

_____

Q2 How many positions have you successfully hired candidates for so far approximately? Please select an answer closest to your experience.

- Less than 5 (4)
- Between 5 and 10 (5)
- Between 11 and 20 (6)
- Between 21 and 30 (7)
- Between 31 and 50 (8)
- Between 51 and 100 (9)
- More than 100 (10)

Q3 How many positions have your participated in the hiring process so far approximately? Please select an answer closest to your experience.

- Less than 5 (1)
- Between 5 and 10 (2)
- Between 11 and 20 (3)
- Between 21 and 30 (4)
- Between 31 and 50 (5)
- Between 51 and 100 (6)
- Between 101 and 200 (7)
- More than 200 (8)

Q4 Please write down the industries in which you did most of your hiring work.

_____

End of Block: attention

Start of Block: data_scientist_remote_exp

Thanks for sharing your experience. Now, we would like to seek your help to design a hiring qualification for a position that our firm is trying to fill up.

Q5 We are trying to hire a Data scientist. A potential candidate can work with our data team for both scientific and commercial research.

Remote work condition:
This position is a remote position. The worker can work anywhere in the world.
and cannot work remotely.

Put yourself in the shoes of a hiring manager, how many years of work experience would you specify for this remote position?

In-person work condition:
This position is an on-site position. The worker must work in-person and cannot work remotely.

Put yourself in the shoes of a hiring manager, how many years of work experience would you specify for this on-site position?

- 0 (7)
- 1-2 years (8)
- 3-5 years (17)
- 5+ years (18)

Q6 Please provide rationale for your selections

_____

_____

_____

_____

_____

Page Break

Q7 Below please select which position did you just specify recruitment qualification for?

- Data scientist—remote work (1)
- Data scientist—in-person (9)
- Marketing analyst—remote work (10)
- Marketing analyst—in-person (11)
- Sale representative—remote work (12)
- Sale representative—in-person (13)

End of Block: data_scientist_remote_exp

Start of Block: demographics

Q8 In your honest opinion, have you answered all questions precisely so that we could use your data in our analysis?

- Yes, I have. You can use my data for sure (1)
- No, I have not and please remove data (4)
- Not sure, maybe or maybe not (5)

Continued on next page

Q9 What gender do you identify as?

- Male (1)
- Female (2)
- Prefer not to answer. (3)

Q10 What is your age?

- 0 - 15 years old (1)
- 16 - 25 years old (2)
- 26 - 35 years old (3)
- 36 - 45 years old (4)
- 46 - 55 years old (5)
- >55 years old (6)

Q11 Please indicate your level of education

- High school or less (1)
- College (current or completed) (2)
- Masters degree (current or completed) (3)
- Professional school (current or completed) (4)
- PhD (current or completed) (5)

Q12 Please indicate your years of hiring experience

- Less than 1 years (1)
- 1-3 years (2)
- 4-6 years (3)
- 7-10 years (4)
- More than 10 years (5)

Q13 Please indicate your country of residency?

- Austria (1)
- Belgium (57)
- Bulgaria (58)
- Croatia (59)
- Cyprus (60)
- Czech Republic (61)
- Denmark (62)
- Estonia (63)
- Finland (64)
- France (65)
- Germany (66)
- Greece (67)
- Hungary (68)
- Ireland (69)
- Italy (70)

- Latvia (71)
- Lithuania (72)
- Luxembourg (73)
- Malta (74)
- Netherlands (75)
- Poland (76)
- Portugal (77)
- Romania (78)
- Slovakia (79)
- Slovenia (80)
- Spain (81)
- Sweden (82)
- United Kingdom (83)
- United States (84)
- Canada (85)

Q14 Please indicate your industry

- Agriculture (1)
- Mining (2)
- Construction (3)
- Manufacturing (4)
- Transportation (5)

- Wholesale Trade (6)
- Retail Trade (7)
- Finance, Insurance and Real Estate (8)
- Services (9)
- Public Administration (10)
- Other (11)

Q15 Please indicate your occupation

- Manager (1)
- Professional (2)
- Technician (3)
- Clerical support worker (4)
- Service and sales worker (5)
- Skilled Agricultural, Forestry and Fishery Worker (6)
- Craft and Related Trades Worker (7)
- Plant and Machine Operator, and Assembler (8)
- Elementary Occupation (9)
- Armed Forces Occupation (10)

Q16 Had experience in remote hiring?

- Yes (1)
- No (2)

Figure M.1: Sample Experiment Design

Table M.1: Prolific Participants' Background

	Prop. of Participants		Prop. of Participants
Gender		**Years of Hiring Experience**	
Women	44%	Less than 1 years	4%
Age		1-3 years	26%
16 - 25 years old	3%	4-6 years	27%
26 - 35 years old	32%	7-10 years	16%
36 - 45 years old	36%	More than 10 years	28%
46 - 55 years old	20%	**Number of positions successfully hired**	
>55 years old	10%	Less than 5	23%
Educational Attainment		Between 5 and 10	29%
High school or less	9%	Between 11 and 20	19%
College Degree	40%	Between 21 and 30	12%
Masters Degree	36%	Between 31 and 50	7%
Professional Degree	10%	Between 51 and 100	5%
PhD degree	5%	More than 100	5%
Industry		**Number of positions participated in hiring**	
Agriculture	0%	Less than 5	19%
Construction	0%	Between 5 and 10	25%
Finance, Insurance and Real Estate	10%	Between 11 and 20	18%
Manufacturing	7%	Between 21 and 30	13%
Mining	0%	Between 31 and 50	10%
Public Administration	11%	Between 51 and 100	6%
Wholesale Trade	1%	Between 101 and 200	4%
Retail Trade	9%	More than 200	4%
Services	15%	**Remote Hiring**	
Transportation	4%	Had remote hiring experience	65%
Other	40%		
Occupation			
Armed Forces Occupation	0%		
Clerical support worker	4%		
Craft and Related Trades Worker	0%		
Elementary Occupation	0%		
Manager	60%		
Plant and Machine Operator, and Assembler	0%		
Professional	29%		
Service and sales worker	3%		
Skilled Agricultural, Forestry and Fishery Worker	0%		
Technician	4%		

Table M.2: Mechanisms Mentioned in Open-Ended Responses by Experimental Condition (N = 344)

Mechanism	In-Person	Remote	Total	% Mentioning
Training / support difficulties	69	117	186	54.1%
Expanded applicant pool	7	21	28	8.1%
Trust / commitment / morality	3	20	23	6.7%
Self-motivation / initiative	2	16	18	5.2%
Collaboration / culture	6	8	14	4.1%