Online Appendices for ”Trusting Talent: Cross-Country Differences in Hiring”

Letian Zhang Shinan Wang

Online Appendix Section A. Sample Distribution

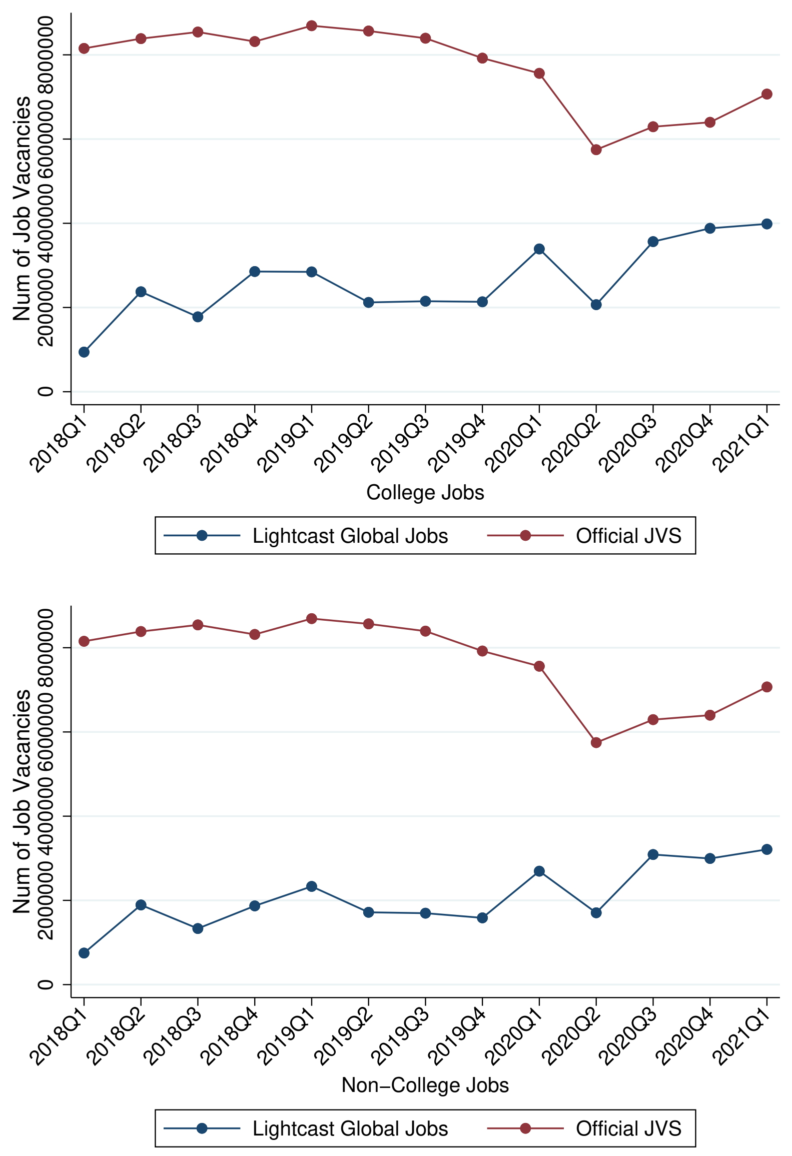


Figure A.1: Number of Job Postings by Quarter

Notes: The figures compare the number of job postings in the Lightcast sample and the number of job openings from Job Vacancy Statistics (JVS) 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 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.

Table A.1: 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.

Table A.2: Number of Job Postings, Sorted by Country

	Complete Sample		Matched Lightcast-Orbis Sample		Foreign Subsidiaries Only	
Austria	1,242,351	2.39%	379,175	2.14%	52,943	2.63%
Belgium	2,396,052	4.61%	895,038	5.06%	202,249	10.03%
Bulgaria	277,635	0.53%	16,426	0.09%	10,898	0.54%
Croatia	70,759	0.14%	25,911	0.15%	7,851	0.39%
Cyprus	12,554	0.02%	501	0.00%	197	0.01%
Czech Republic	283,897	0.55%	99,957	0.56%	17,018	0.84%
Denmark	65,748	0.13%	19,040	0.11%	835	0.04%
Estonia	72,174	0.14%	19,540	0.11%	11,449	0.57%
Finland	140,561	0.27%	119,484	0.68%	20,550	1.02%
France	9,774,007	18.82%	2,160,649	12.21%	267,975	13.29%
Germany	16,000,000	30.82%	5,831,194	32.95%	542,479	26.91%
Greece	73,428	0.14%	11,896	0.07%	3,215	0.16%
Hungary	134,877	0.26%	3,794	0.02%	2,025	0.10%
Ireland	894,804	1.72%	140,338	0.79%	53,514	2.65%
Italy	4,024,687	7.75%	1,501,520	8.48%	182,600	9.06%
Latvia	84,291	0.16%	54,361	0.31%	20,614	1.02%
Lithuania	145,043	0.28%	17,424	0.10%	7,287	0.36%
Luxembourg	60,298	0.12%	3,556	0.02%	2,104	0.10%
Malta	7,552	0.01%	98	0.00%	7	0.00%
Netherlands	2,108,382	4.06%	319,959	1.81%	23,036	1.14%
Poland	788,204	1.52%	247,065	1.40%	106,198	5.27%
Portugal	453,379	0.87%	44,180	0.25%	17,120	0.85%
Romania	239,656	0.46%	43,286	0.24%	25,255	1.25%
Slovakia	43,784	0.08%	31,551	0.18%	12,804	0.64%
Slovenia	31,334	0.06%	11,723	0.07%	4,333	0.21%
Spain	2,186,997	4.21%	295,863	1.67%	63,782	3.16%
Sweden	1,427,650	2.75%	698,696	3.95%	67,331	3.34%
United Kingdom	8,908,634	17.16%	4,705,220	26.59%	290,093	14.39%
Total	51,921,232	100.00%	17,697,444	100.00%	2,015,762	100.00%

Table A.3: Descriptive Statistics (Cross-Country Sample)

	Mean	SD	Min	Max
Foundational Skill Level	3.44	0.57	1.00	4.82
Social Trust (Local Country)	0.32	0.16	0.08	0.70
Job Req. College Degree	0.10	0.30	0.00	1.00
Job Req. Graduate Degree	0.05	0.23	0.00	1.00
Job Req. Short-Cycle Tertiary Degree	0.38	0.49	0.00	1.00
Job Req. Non-Tertiary Degree	0.46	0.50	0.00	1.00
Job Req. Work Experience	0.53	0.50	0.00	1.00
Num of Skills Listed (log)	2.03	1.03	0.00	5.17
Human Capital Index (Local Country)	0.75	0.05	0.60	0.81
GDP per Capita(log) (Local Country)	10.17	0.67	8.83	11.56
Rule of Law (Local Country)	1.09	0.59	-0.01	2.05
Vocational Education(%) (Local Country)	0.48	0.16	0.17	0.71
Collective Bargaining(%) (Local Country)	0.56	0.28	0.00	0.98
Unemployment Rate (Local Country)	0.06	0.03	0.02	0.16

Pairwise Correlation (Cross-Country Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Foundational Skill Level	1.00													
Social Trust (Local Country)	0.06	1.00												
Job Req. College Degree	-0.09	-0.00	1.00											
Job Req. Graduate Degree	-0.03	-0.06	-0.08	1.00										
Job Req. Short-Cycle Tertiary Degree	0.03	-0.25	-0.26	-0.20	1.00									
Job Req. Non-Tertiary Degree	0.03	0.28	-0.29	-0.22	-0.72	1.00								
Job Req. Work Experience	-0.05	0.02	0.09	0.06	-0.14	0.07	1.00							
Num of Skills Listed (log)	-0.20	0.12	0.16	0.06	-0.20	0.09	0.31	1.00						
Human Capital Index (Local Country)	0.06	0.60	-0.15	-0.05	0.20	-0.09	-0.08	0.01	1.00					
GDP per Capita(log) (Local Country)	0.10	0.48	-0.08	0.03	0.14	-0.11	-0.02	0.03	0.64	1.00				
Rule of Law (Local Country)	0.11	0.50	-0.11	-0.02	0.24	-0.16	-0.01	0.13	0.59	0.56	1.00			
Vocational Education(%) (Local Country)	-0.00	-0.06	-0.04	0.03	0.03	-0.02	-0.10	-0.26	0.05	-0.07	-0.18	1.00		
Collective Bargaining(%) (Local Country)	0.05	-0.18	-0.09	0.12	0.27	-0.28	-0.12	-0.34	-0.15	0.32	-0.16	0.21	1.00	
Unemployment Rate (Local Country)	-0.04	-0.21	0.13	0.05	-0.16	0.06	0.06	-0.11	-0.53	-0.07	-0.59	-0.19	0.59	1.00

Table A.4: Descriptive Statistics (Bilateral Country Sample)

	Mean	SD	Min	Max
Foundational Skill Level	3.42	0.56	1.00	4.82
Social Trust (HQ Country to Local Country)	2.69	0.31	1.94	3.57
Job Req. College Degree	0.12	0.33	0.00	1.00
Job Req. Graduate Degree	0.08	0.27	0.00	1.00
Job Req. Short-Cycle Tertiary Degree	0.41	0.49	0.00	1.00
Job Req. Non-Tertiary Degree	0.38	0.49	0.00	1.00
Job Req. Work Experience	0.53	0.50	0.00	1.00
Num of Skills Listed (log)	2.03	1.01	0.00	5.02
Diff. in GDP per Capital (log) (HQ-Local)	9.61	1.04	5.99	11.49
Common Legal Origin (HQ-Local)	0.18	0.39	0.00	1.00
Physical Distance (log) (HQ-Local)	6.98	0.59	4.89	8.02

Pairwise Correlation (Bilateral Country Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Foundational Skill Level	1.00										
Social Trust (HQ Country to Local Country)	0.15	1.00									
Job Req. College Degree	-0.06	-0.01	1.00								
Job Req. Graduate Degree	-0.03	0.02	-0.11	1.00							
Job Req. Short-Cycle Tertiary Degree	0.06	0.08	-0.31	-0.25	1.00						
Job Req. Non-Tertiary Degree	-0.01	-0.08	-0.28	-0.22	-0.65	1.00					
Job Req. Work Experience	-0.03	0.02	0.11	0.12	-0.08	-0.05	1.00				
Num of Skills Listed (log)	-0.16	-0.01	0.11	0.09	-0.06	-0.06	0.30	1.00			
Diff. in GDP per Capital (log) (HQ-Local)	0.02	-0.02	-0.05	-0.10	-0.05	0.14	-0.10	-0.10	1.00		
Common Legal Origin (HQ-Local)	0.06	0.35	0.05	0.00	-0.03	-0.01	0.03	0.00	-0.14	1.00	
Physical Distance (log) (HQ-Local)	-0.10	-0.27	0.05	-0.09	-0.20	0.23	-0.06	-0.01	0.04	-0.19	1.00

Online Appendix Section B. Matching Lightcast with Orbis to Identify Multinational Firms

An important step in our data cleaning is to identify multinational organizations and their headquarters. To do so, we merge our Lightcast European job postings with the Orbis database, which collects data from over 160 government and commercial information providers, covering more than 100 countries and over 400 million firms as of July 2022. For most European countries, where reporting to the national business registers is mandatory, Orbis has the same coverage as the national statistical office because it uses the same sources. The database covers public and private firms and includes detailed information on their location, industry, and domestic and foreign owners and subsidiaries, allowing us to observe global interconnections between the firms in our sample (Kalemli-Ozcan et al. 2015).

The Orbis database includes more than 400 million employers and our Lightcast sample contains more than 3.8 million employers. To make the matching process more manageable, we limit the Orbis sample to those firms with more than 10 employees in the European Union (EU) countries, which reduces the pool of available firms in Orbis to 1.6 million. Our assumption is that firms with fewer than 10 employees are unlikely to be multinational employers.

Our matching is based on employer name, industry, and country. After collecting a job posting, Lightcast's research team uses proprietary algorithms to identify its employer name, industry (NACE level 2), and location (country and local region). In the first step, we standardize the Lightcast employer names by removing common company suffixes such as "Inc," "Ltd," and "Gmbh." We then match employer names in Lightcast and Orbis and identify those with the same standardized name, industry code, and country. The country name is the country in which the job is posted. Since the Orbis database includes separate entries for each foreign subsidiary of a multinational organization, we can match the job postings to specific foreign subsidiaries. Out of the 50 million job postings, 13.6 million can be matched exactly based on these criteria.

In the next step, we relax the criteria for exact standardized employer name, since the employer name could be spelled in different ways (e.g., *GVF VersicherungsMakler AG* versus *GVF VersicherungsMakler Aktiengesellschaft*). We use the *matchit* package in Stata to calculate a similarity score between every Lightcast employer name and every Orbis firm name that have the same industry and country location. After manually checking many observations at different score levels, we decided to keep all pairs that have a similarity score above 0.65, as pairs below this score are extremely unlikely to be correctly matched. We got 3,933,757 such pairs. We keep all pairs with the same industry code and country location; for each Lightcast employer name, we keep the top five possible matches to the Orbis employer name, sorted by similarity score. This leaves a sample of 162,258 such pairs. With the help of two research assistants, we manually checked each one and used our judgment to determine which pairs are correctly matched. In this process, our priority was avoiding false positives: we determined a pair to be matched only if we were very certain. Overall, this matching process gives us a sample of more than 17 million job postings from 355,997 firms headquartered in 144 countries.

Online Appendix Section C. Coding Skills in Lightcast Job Postings

This section provides more details on Lightcast's coding of skill requirements and the comparison between Lightcast's coding and O*NET's ratings. Skill requirements are included in most job postings (see Online Appendix Figure C.1 for examples). Lightcast's skill coding is based on ESCO level-3 skills, a skill categorization system widely used in Europe. There are 13,890 ESCO skills, ranging from widely used soft skills such as *work in teams* to more specific technical skills such as *ICT system programming* and *JavaScript*. Using these as the list of possible skills, Lightcast's research team tries to assess whether or not each of these skills is mentioned in a job posting.

[Insert Online Appendix Figure C.1 about here]

Lightcast's ontology team focusing on European job postings includes over 30 experts, including HR specialists, academics, and government ministers. More than half have a PhD and five are fulltime Lightcast employees. There is at least one native speaker for each language used in our job-posting sample, including regional languages such as Catalan. Starting in 2017, the team began to create rule-based dictionaries for each language. These were continuously updated and revised till our data extraction in 2021. These dictionaries are based on an elaborate set of linguistic rule-based classifiers, comprising thousands of rules (including numerous neighborhood and negation rules) and keywords. These rules allows the team to distinguish skills described with similar words; for example, those that use *model* to refer to a business plan and those that use it to refer to a software development tool.

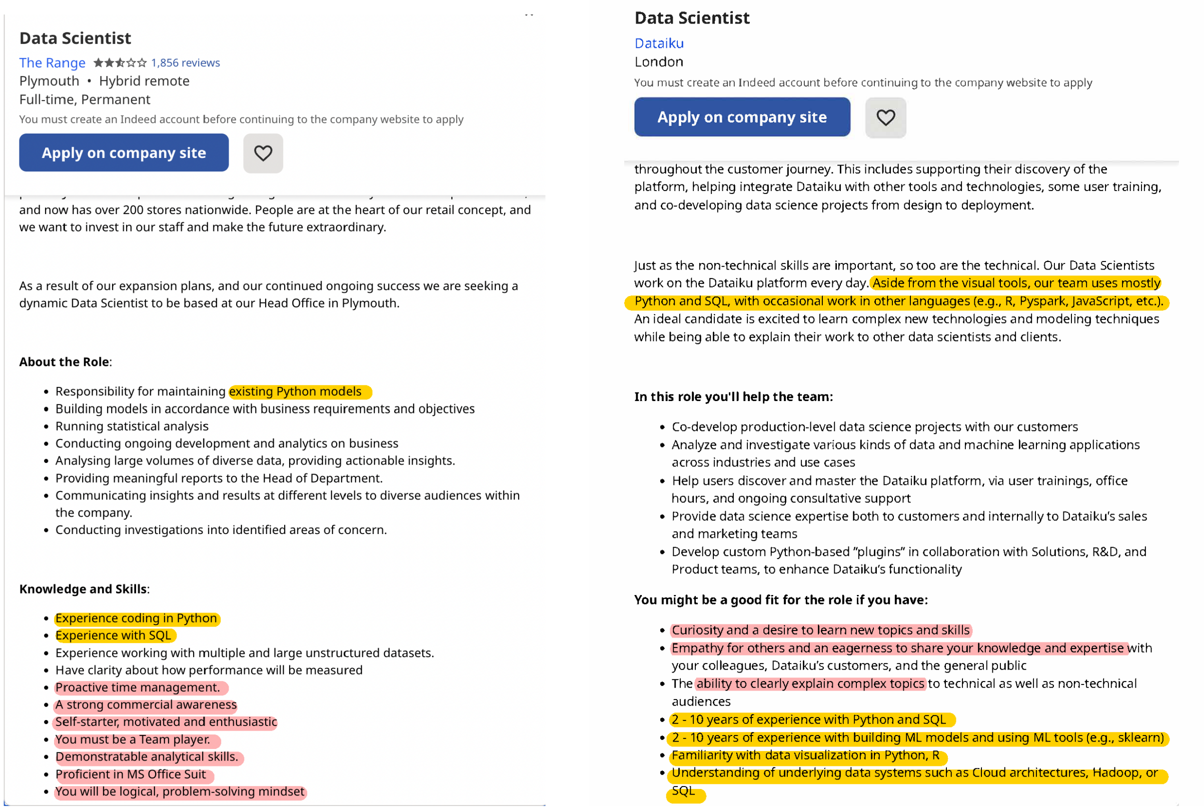
Using this method, the Lightcast team identifies all the ESCO skills required in each job posting. The median job posting lists seven required skills; 17 percent list zero skills and 47 percent require more than ten. Some countries tend to list more or fewer skills: the averages for Ireland, the United Kingdom, and Luxembourg are above 20 while the averages for Slovenia, Finland, Croatia, and Estonia are below five.

To validate Lightcast's skill-coding, we aggregate Lightcast skill requirements to the occupation level and compare them to the ratings provided by the Occupational Information Network (O*NET) system developed by the US Bureau of Labor Statistics. O*NET was first published in 1998 and has been continuously updated. It provides information for around 1000 SOC occupations and rates each on a variety of dimensions. These ratings are based on representative surveys of employees in each occupation and supplemented by selected experts' opinions.

Specifically, O*NET rates each occupation in terms of skills, abilities, interests, knowledge, work activities, work context, work style, and work values. For simplicity, we use O*NET skill ratings for validation, although the other seven categories could also contain what we typically describe as skills. O*NET covers 25 skill categories and we manually coded all the ESCO skills to match them to one of these 25 broad skill categories. Since ESCO skill categories and O*NET skill categories are designed differently, the matching is not always perfect. Some ESCO skills could fall into multiple O*NET categories. In the end, we identify 15 broad skill categories for which there is relatively high compatibility between ESCO's and O*NET's coding systems. They 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 of these categories, we calculate the proportion of jobs in each Lightcast occupation that require a skill in that category. We then compare this proportion to O*NET's rating in that skill category for that occupation.

Online Appendix Figure C.2 shows the correlation between Lightcast's coding and O*NET's skill rating across occupations for each of these 15 skill categories. The correlations are all positive and moderately strong. On the higher end, for skill categories such as programming and complex problem solving, the correlation between the proportion of Lightcast jobs with that skill and O*NET's rating of that skill is above 0.45. Even on the lower end, for skill categories such as instructing and service orientation, the correlations exceed 0.3. These moderately high correlations help corroborate the validity of Lightcast's skill coding. The remaining differences between the two rating systems could be due to cross-country differences, errors, and noise in both ratings and to different skill categorizations.

[Insert Online Appendix Figure C.2 about here]



Data Scientist

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Full-time, Permanent

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and now has over 200 stores nationwide. People are at the heart of our retail concept, and we want to invest in our staff and make the future extraordinary.

As a result of our expansion plans, and our continued ongoing success we are seeking a dynamic Data Scientist to be based at our Head Office in Plymouth.

About the Role:

- Responsibility for maintaining existing Python models
- Building models in accordance with business requirements and objectives
- Running statistical analysis
- Conducting ongoing development and analytics on business
- Analysing large volumes of diverse data, providing actionable insights.
- Providing meaningful reports to the Head of Department.
- Communicating insights and results at different levels to diverse audiences within the company.
- Conducting investigations into identified areas of concern.

Knowledge and Skills:

- Experience coding in Python
- Experience with SQL
- Experience working with multiple and large unstructured datasets.
- Have clarity about how performance will be measured
- Proactive time management.
- A strong commercial awareness
- Self-starter, motivated and enthusiastic
- You must be a Team player.
- Demonstratable analytical skills.
- Proficient in MS Office Suit
- You will be logical, problem-solving mindset

(a) Job Focused on Foundational Skills

Data Scientist

Dataiku

London

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Apply on company site

throughout the customer journey. This includes supporting their discovery of the platform, helping integrate Dataiku with other tools and technologies, some user training, and co-developing data science projects from design to deployment.

Just as the non-technical skills are important, so too are the technical. Our Data Scientists work on the Dataiku platform every day. Aside from the visual tools, our team uses mostly Python and SQL, with occasional work in other languages (e.g., R, Pyspark, JavaScript, etc.). An ideal candidate is excited to learn complex new technologies and modeling techniques while being able to explain their work to other data scientists and clients.

In this role you'll help the team:

- Co-develop production-level data science projects with our customers
- Analyze and investigate various kinds of data and machine learning applications across industries and use cases
- Help users discover and master the Dataiku platform, via user trainings, office hours, and ongoing consultative support
- Provide data science expertise both to customers and internally to Dataiku's sales and marketing teams
- Develop custom Python-based "plugins" in collaboration with Solutions, R&D, and Product teams, to enhance Dataiku's functionality

You might be a good fit for the role if you have:

- Curiosity and a desire to learn new topics and skills
- Empathy for others and an eagerness to share your knowledge and expertise with your colleagues, Dataiku's customers, and the general public
- The ability to clearly explain complex topics to technical as well as non-technical audiences
- 2 - 10 years of experience with Python and SQL
- 2 - 10 years of experience with building ML models and using ML tools (e.g., sklearn)
- Familiarity with data visualization in Python, R
- Understanding of underlying data systems such as Cloud architectures, Hadoop, or SQL

(b) Job Focused on Advanced Skills

Figure C.1: Examples of Job Postings

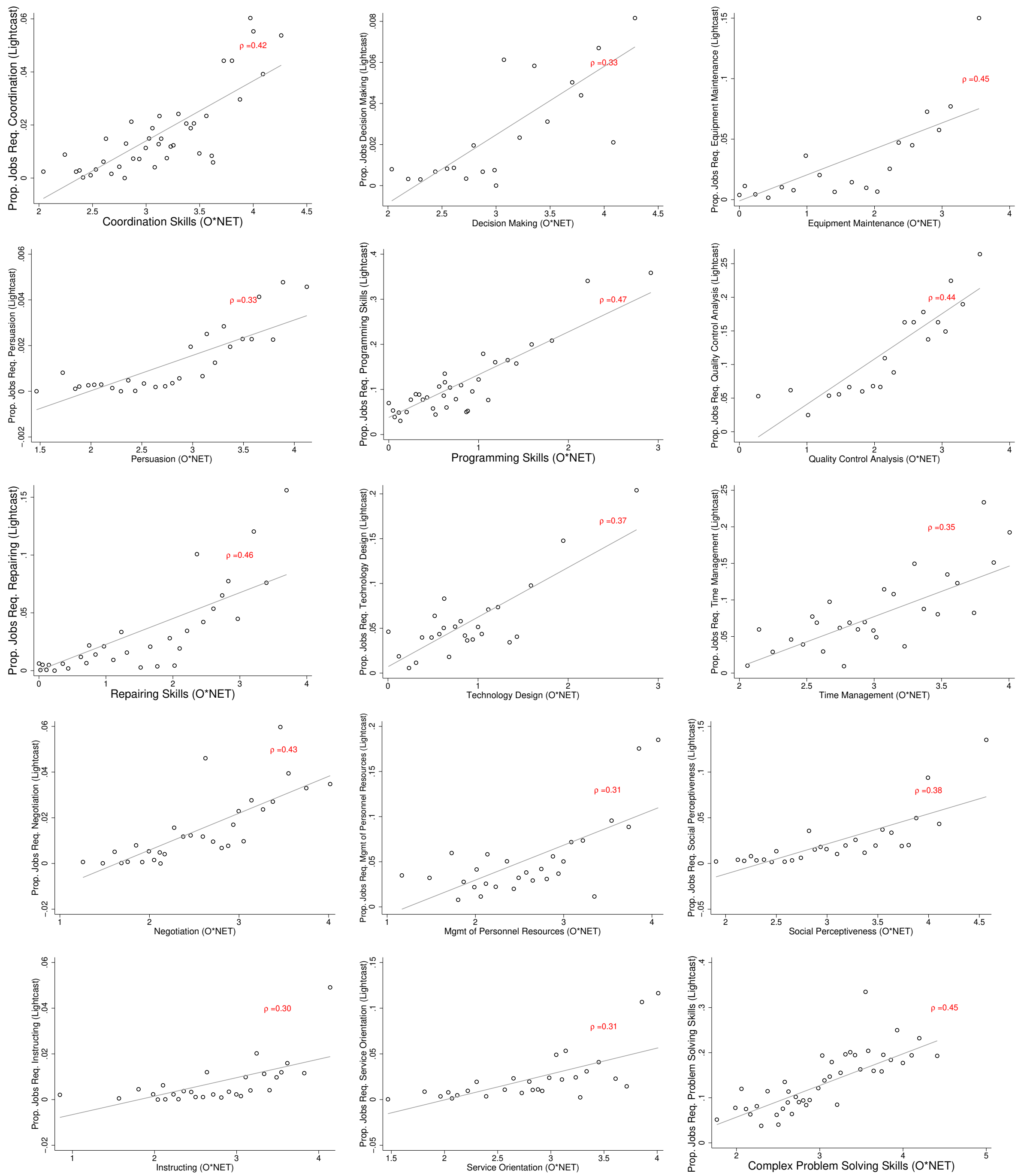
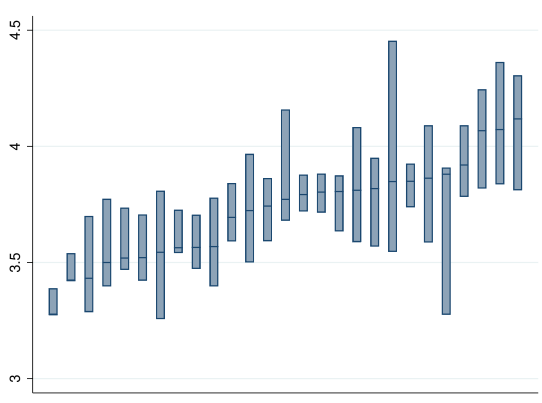
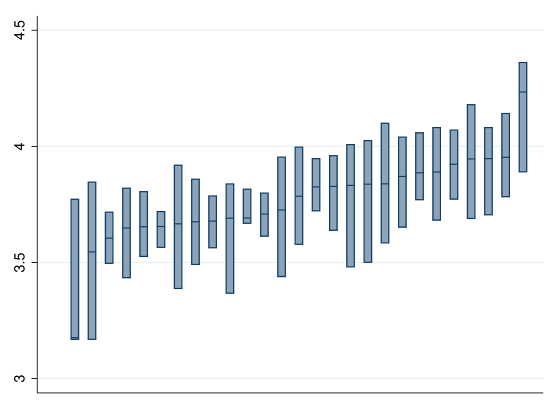


Figure C.2: Comparing Lightcast Skills and O*NET ratings

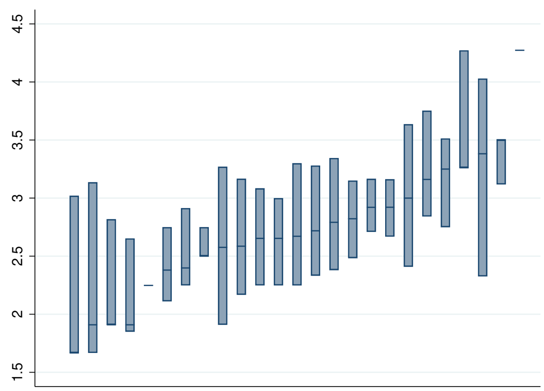
Notes: We compare the skills parsed by Lightcast to O*NET ratings at the occupation level. We use the international standard classification of occupations (ISCO) and have 440 occupations. The Lightcast research team codes the skills listed on each job posting. We aggregate job postings to the occupation 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's skill classification. We manually match Lightcast skills to one of these 15 categories. For example, the O*NET category "complex problem solving" is matched to the following ESCO skills: "address problems critically," "complex problems," "create solutions to problems," "develop work plans to solve problems," "problem definition," "problem-solving," "solve ICT system problems," "solve problems in healthcare," and "solve technical problems." 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 binscatter to plot the correlation between Lightcast skill codings and O*NET skill ratings.



(a) Shop Sales Assistant



(b) Executive secretaries



(c) Electrical mechanics

Figure C.3: Skill Preference by Occupation

Notes: The figures show employers' preferences for foundational vs. advanced skills for (a) shop sales assistants, (b) executive secretaries, and (c) electrical mechanics across 28 EU countries. Employers' skill preference is at the job-posting level. For each posting, Lightcast parses the skills listed. We conduct surveys to measure where each skill sits on the foundational–advanced scale and take the average value across all skills in a posting. We plot each job's foundational vs. advanced skill preferences at the 25th percentile (lower hinge of the box), the median, and the 75th percentile (upper hinge of the box). The higher the value on the y-axis, the more a posting lists foundational instead of advanced skills.

Online Appendix Section D. Validating the Concept of Foundational and Advanced Skills

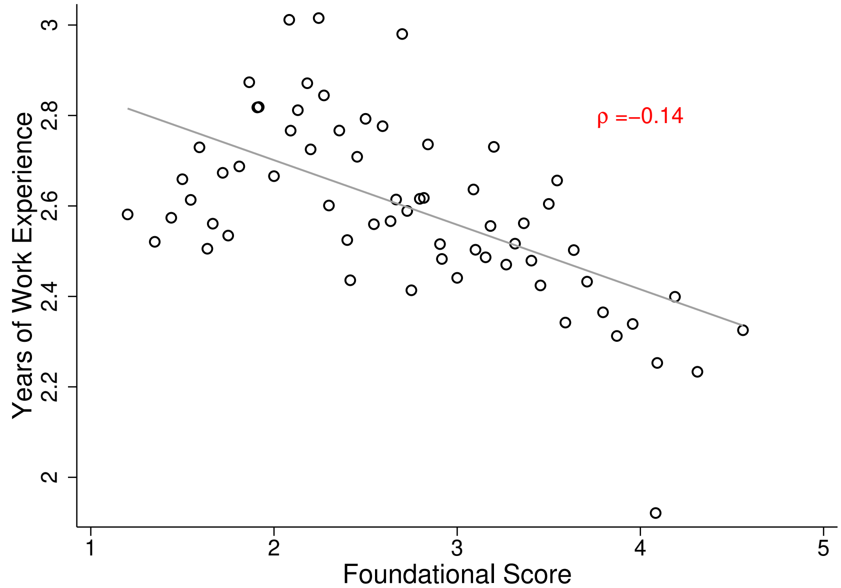
This appendix section validates the concept of foundational and advanced skills. Foundational skills are those requiring fewer prerequisites to learn, while advanced skills require more prerequisites. We use an online survey to place all skills on a continuous spectrum, from most-foundational to most-advanced. To validate this construct, we compare each skill's foundational score with its requirements for job preparation and average years of work experience. The more "advanced" the skill, the more preparation and experience it should require.

First, for each skill, we examine all job postings in our sample that require this skill and average the required years of work experience. Online Appendix Figure D.1a plots the correlation between a skill's position on the foundational–advanced spectrum and its average required years of work experience. Consistent with our expectation, we find a strong linear relationship: more-foundational skills require less experience.

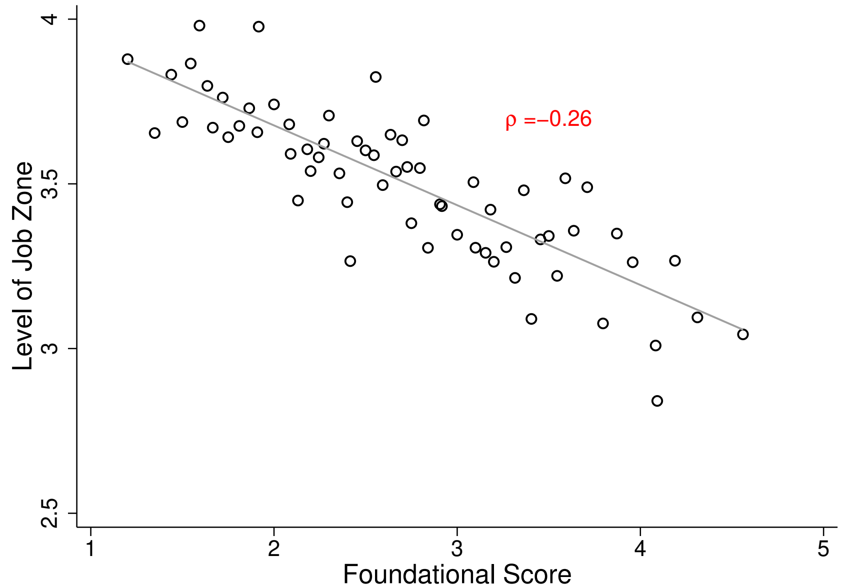
[Insert Online Appendix Table D.1a about here]

Second, we compare O*NET's job-preparation levels to a skill's position on our foundational–advanced scale. O*NET's job zones categorize occupations based on their specific preparation requirements, ranging from Zone 1 for jobs requiring minimal formal training to Zone 5 for occupations demanding extensive training and experience. These job zones are available for each O*NET occupation. As before, we aggregate a skill's average preparation level by measuring the average preparation level for all occupations including that skill. As Online Appendix Figure D.1b shows, a more foundational skill is associated with less preparation.

[Insert Online Appendix Table D.1b about here]



(a) Correlation with Work Experience



(b) Correlation with Job Zone

Figure D.1: Comparing Foundational Score with Other Skill Characteristics

Notes: These two figures show the correlation between ESCO skills' foundational score and (a) their work-experience requirement and (b) job-zone level. Each ESCO skill is a unit of observation. Foundational score comes from our self-administered online survey. For each skill, its work-experience requirement is the average years of work experience required for all jobs that list that skill. Its job-zone level is the average O*NET job-zone level for all jobs that list that skill.

Online Appendix Section E. Measures of Generalized Trust

The European Values Study (EVS) is a large-scale longitudinal survey administered every nine years that covers an increasing number of countries. It is a random-sample survey, which gives full coverage of the target population aged 18 years or older and living in private households, regardless of nationality or language. Respondents are interviewed face-to-face for approximately one hour. The EVS provides insights into the ideas, beliefs, preferences, attitudes, values, and opinions of residents all over Europe. Topics include how Europeans think about life, family, work, religion, politics, and society (EVS, 2017).

There are five waves of EVS surveys currently available, taken in 1981, 1990, 1999, 2008, and 2017. In total, they cover more than 223,000 respondents from 48 countries/regions, including all 28 EU countries in our Lightcast sample. The exact question we use is: "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?" Respondents can select one of two options: "Most people can be trusted" or "Can't be too careful." For each country, we measure social trust as the number of people in that country choosing the option "Most people can be trusted" over the number who answered the question.

Another way to measure a country's generalized trust is the World Values Survey (WVS), a global survey of basic values and beliefs in over 100 countries. It, too, is a nationally representative survey, as it uses a stratified multistage random-sampling approach in each country. Unlike the EVS, however, the WVS does not cover all 28 EU countries in our sample. In particular, it does not cover Austria, Belgium, Denmark, Ireland, Luxembourg, Malta, and Portugal. For the remaining 21 countries, the WVS asks respondents the following question: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" Respondents can choose one of three answers: "Most people can be trusted," "Need to be very careful," or "Don't know." This question was asked in all seven waves of the WVS since 1981. We measure a country's social trust as the number of respondents in that country choosing the option "Most people can be trusted" over the number who chose either that option or "Need to be very careful."

Online Appendix Table E.1 compares the social-trust measure calculated using the EVS and that calculated using the WVS in our 21 EU countries. In this comparison, we aggregated responses from all waves, since the two surveys have similar time frames. As the figure shows, results from the two surveys are highly consistent, with a correlation of over 0.9. Not surprisingly, we produce the same set of conclusions when using WVS in place of EVS to measure social trust.

[Insert Online Appendix Table E.1 about here]

In calculating social trust, we combined different waves of EVS. An important assumption is that a country's social trust does not change significantly (Gauchat 2012; Kwon, Heflin, and Ruef 2013). This is validated in Online Appendix Table E.2, in which we compare each country's social trust in the 1980s to that in the 2010s, based on the EVS survey. We find a correlation of over 0.9, suggesting that country-level social trust is highly stable.

[Insert Online Appendix Table E.2 about here]

Despite the widespread use of the survey-based trust measures, there is growing doubt about the validity and equivalence of conventional measures of generalized trust. For example, Nannestad (2008) reviews the limitations of using survey-based studies to measure generalized trust; one major issue is the wording of the question, which doesn't specify the parties involved and the matters about which they are to be trusted or not. To address these concerns, Robbins (2022, 2023) develops two novel trust measures—the Stranger Face Trust scale (SFT) and the Imaginary Stranger Trust scale (IST). These are assessed in a person-specific and domain-specific manner, capturing the average trust across a variety of situations, trustees, behaviors, and contexts. Similarly, Delphy, Newton, and Welzel (2011) and van Hoorn (2014) question the validity of the standard survey question's use of "most people." They emphasize the importance of considering the width of the imagined circle of "most people" and point out that the radius of "most people" varies considerably across countries.

To better alleviate some of these concerns, we validate the survey-based trust measure using a standard economic experiment commonly referred to as the "trust game" (Berg, Dickhaut, and

McCabe 1995). In this two-party game, the "trustor" is given a choice of sending some, all, or none of his or her $1 experimental payment to an anonymous partner, the "trustee." The experimenter then triples any money sent. The trustee then decides how much of his or her total wealth (up to $4) to return to the trustor. Our focus is solely on measuring trust and not reciprocity, so all participants were assigned the role of trustor. At the end of the experiment, they were paid based on a random-number generator whose distribution follows standard trustee responses from previous studies.

Using the online platform Prolific, we conducted a lab experiment with 1,173 participants from 20 countries, with 60 respondents per country except for Denmark where we had 33 participants. We had difficulty recruiting people in eight smaller EU countries: Bulgaria, Cyprus, Croatia, Lithuania, Luxembourg, Malta, Romania, and Slovakia.

Our trust game followed Berg, Dickhaut, and McCabe's (1995) experiment design. Participants were provided with instructions and asked to make a decision: "You will play this game with a randomly assigned Prolific participant in your country. You will enter your decision as Player A, and a randomly assigned participant will see your choice a few days later and play the role of Player B. As Person A, what amount would you like to give to Person B? You will be rewarded real money for the final payoff." Respondents were given the option to choose any amount from $0 to $1 in increments of $0.1.

We then calculated the average dollar amount given by our participants in each country. The correlation between the trust measure based on our trust-game lab experiment and that based on EVS trust surveys is 0.7. Since this correlation is not as high as we would like, we conducted an additional analysis using the trust measure from our trust game experiment as the main independent variable. Online Appendix Table E.1 shows results substantively similar to those in Table 1.

[Insert Online Online Appendix Table E.1 about here]

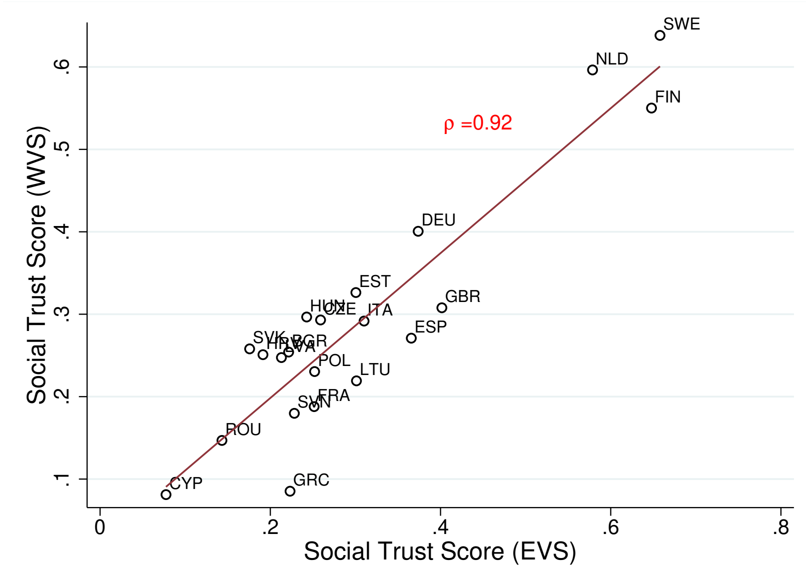


Figure E.1: Comparing European Values Study and World Values Survey

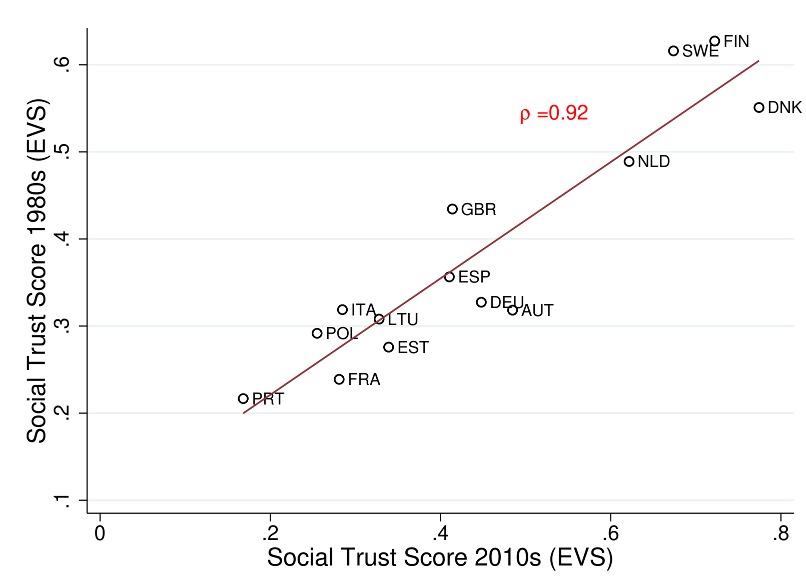


Figure E.2: Temporal Trend in Social Trust

Notes: Figure E.1 compares country-level social trust calculated by the European Values Study (EVS) and the World Values Survey (WVS). Both the EVS and WVS have the question ”Most people can be trusted” and we calculate the proportion of people answered ”most people can be trusted” over all those who answered the question. 21 EU countries are covered by both the EVS and WVS, we plot the social trust measures derived from both surveys. Figure E.2 compares social trust scores derived from the EVS in the 1980s and those in the 2010s. The 1980s EVS survey wave took place between 1980 and 1984, the 2010s EVS survey wave took place between 2017 and 2020.

Table E.1: Linear Estimation Predicting Preference for Foundational Skills: Using Trust Game Measures

	Complete Sample			Matched Sample (With Orbis)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social Trust: Trust Game Measure	1.330	1.126	0.449	0.360	0.484	0.503	0.338
	(0.326)	(0.269)	(0.134)	(0.378)	(0.296)	(0.258)	(0.183)
Job Req. College Degree		-0.0198	0.00442	-0.0435	0.00532	-0.00500	-0.00529
		(0.0256)	(0.0175)	(0.0296)	(0.0165)	(0.0151)	(0.0154)
Job Req. Graduate Degree		0.0155	0.00452	-0.0186	0.0105	-0.00124	-0.00215
		(0.0232)	(0.0132)	(0.0203)	(0.0128)	(0.0103)	(0.0104)
Job Req. Short-Cycle Tertiary Degree		0.00464	-0.0116	-0.0276	-0.0141	-0.0150	-0.0157
		(0.0199)	(0.0106)	(0.0119)	(0.00820)	(0.00882)	(0.00884)
Job Req. Non-Tertiary Degree		0.00719	0.0120	0.00521	-0.00263	0.00530	0.00543
		(0.0222)	(0.00923)	(0.0166)	(0.0108)	(0.00881)	(0.00875)
Job Req. Work Experience		0.00837	0.00528	0.0271	0.0149	0.00769	0.00761
		(0.00984)	(0.00833)	(0.0172)	(0.00764)	(0.00555)	(0.00556)
Num. of Skills (log)		-0.0209	-0.0307	-0.133	-0.0662	-0.0327	-0.0330
		(0.0120)	(0.0126)	(0.0205)	(0.0169)	(0.0175)	(0.0175)
GDP per Capita (log) (Local Country)			0.186				0.199
			(0.0396)				(0.0408)
Human Capital Index (Local Country)			-0.974				-0.859
			(0.351)				(0.646)
Rule of Law (Local Country)			0.0413				-0.0156
			(0.0205)				(0.0238)
Unemployment Rate (Local Country)			-1.000				-0.0550
			(0.170)				(0.326)
% of Graduates from Vocational Education (Local Country)			-0.0677				-0.0709
			(0.0628)				(0.0561)
Collective Bargining Coverage (Local Country)			0.0492				0.0346
			(0.0282)				(0.0543)
Observations	51063949	50599917	48699366	14687435	14583483	14660697	14660697
R^2	0.012	0.298	0.335	0.244	0.416	0.597	0.598
Fixed Effects:							
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation		Yes			Yes		
Occupation x Sector			Yes				
Employer				Yes	Yes		
Occupation x Employer						Yes	Yes

Standard errors in parentheses
$p < 0.05$, $p < 0.01$, $p < 0.001$

Notes: These models use the same model specification as in Table 2. Instead of measuring social trust using surveys, we conduct online trust games in 20 countries to measure social trust. Standard errors clustered at the country level are in parentheses.

Online Appendix Section F. Measure of Bilateral Trust

Measures of Bilateral Trust An important independent variable is bilateral trust between countries; that is. the amount of generalized trust that people from one country have in people from a given other country. We measure bilateral trust among European countries using the Eurobarometer surveys, designed to monitor the social and political attitudes of citizens of the European Union. Since 1970, they have been conducted annually on a representative sample of people over 16 years old. Each survey samples about 1,000 people per country; the list of covered countries varies slightly from year to year. Coverage has increased from five countries in 1970 to 16 in the late 1990s.

The survey question we use is: “I would like to ask you (a question) about how much trust you have in people from various countries.” Respondents were asked, regarding each country on a list of countries, their trust level on a four-point scale: “lots of trust,” “some trust,” “not very much trust,” and “no trust at all.” This question was asked in 1970, 1976, 1980, 1982, 1986, 1990, 1991, and every year from 1993 to 1996. As with generalized trust, we could measure bilateral trust using either responses from the latest survey wave or aggregated responses from all waves. Whether or not to combine the waves largely depends on how much bilateral trust changes over time. As Online Appendix Figure F.1 shows, bilateral trust measures in the 1970s and in the 1990s are highly correlated, with a correlation of over 0.8. This suggest that bilateral trust, like generalized trust, is highly stable. We therefore aggregate responses from all survey waves to create our bilateral-trust measures, an approach consistent with previous studies (e.g., Guiso, Sapienza, and Zingales 2009).

[Insert Online Appendix Figure F.1 about here]

The Eurobarometer survey asks respondents to indicate their bilateral trust on a four-point scale. We averaged the responses such that bilateral trust ranges from 1 to 4. Alternative approaches are to calculate (a) the proportion of individuals answering “lots of trust” and (b) the proportion answering either “lots of trust” or “some trust.” Measures using these approaches produce results very similar to those of our main approach of using a four-point scale, with correlations over 0.9.

We focus on bilateral trust toward people of the EU countries in our job-posting sample. The Eurobarometer surveys ask respondents about their trust in people from 29 countries, including 24 European countries, the United States, China, Russia, Japan, and Turkey. Of the 24 European countries, 21 are in our job-posting sample: Austria, Belgium, Bulgaria, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden, and the UK. The Eurobarometer surveys in 16 European countries—Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, and the UK—include the bilateral-trust question and our sample includes employers headquartered in all of those. We therefore have 336 bilateral dyads (16 x 21 = 336) and bilateral-trust measures.

One concern with Eurobarometer's bilateral-trust measures is that they were conducted from 1970 to 1996, whereas our job-posting sample is mostly from 2018 to 2021. This two-decade gap could introduce temporal mismatch if bilateral trust shifted since the 1990s. To address this issue, we administered a cross-country survey in 2023 to replicate the bilateral-trust measure. Using the online platform Prolific, we surveyed 1,173 people in 20 countries, with 60 respondents per country except for Denmark where we had 33.

In this self-administered survey, we followed exactly the same design as the Eurobarometer surveys, asking: "I would like to ask you (a question) about how much trust you have in people from various countries." Respondents again could choose: "lots of trust," "some trust," "not very much trust," or "no trust at all." We averaged the trust scores for each country-to-country dyad to replicate the bilateral-trust measure. As Online Appendix Table F.2 shows, the correlation between the bilateral-trust measure based on our survey and that based on Eurobarometer surveys is around 0.6. Since this correlation is not as high as we would like, we conduct an additional analysis using our self-administered bilateral-trust measures as the main independent variable. Online Appendix Table F.1 shows results substantively similar to those in Table 2, with comparable effect size.

[Insert Online Appendix Figure F.2 and Online Appendix Table F.1 about here]

Figure F.1: Correlation between Bilateral Trust 1970 and 1990

Notes: The figure plots Eurobarometer's bilateral trust measures in the 1970s and 1990s. The unit of observation is country dyad. We averaged the bilateral trust level in the 1970s and then in the 1990s and plot their correlation using the Stata command *binscatter*.

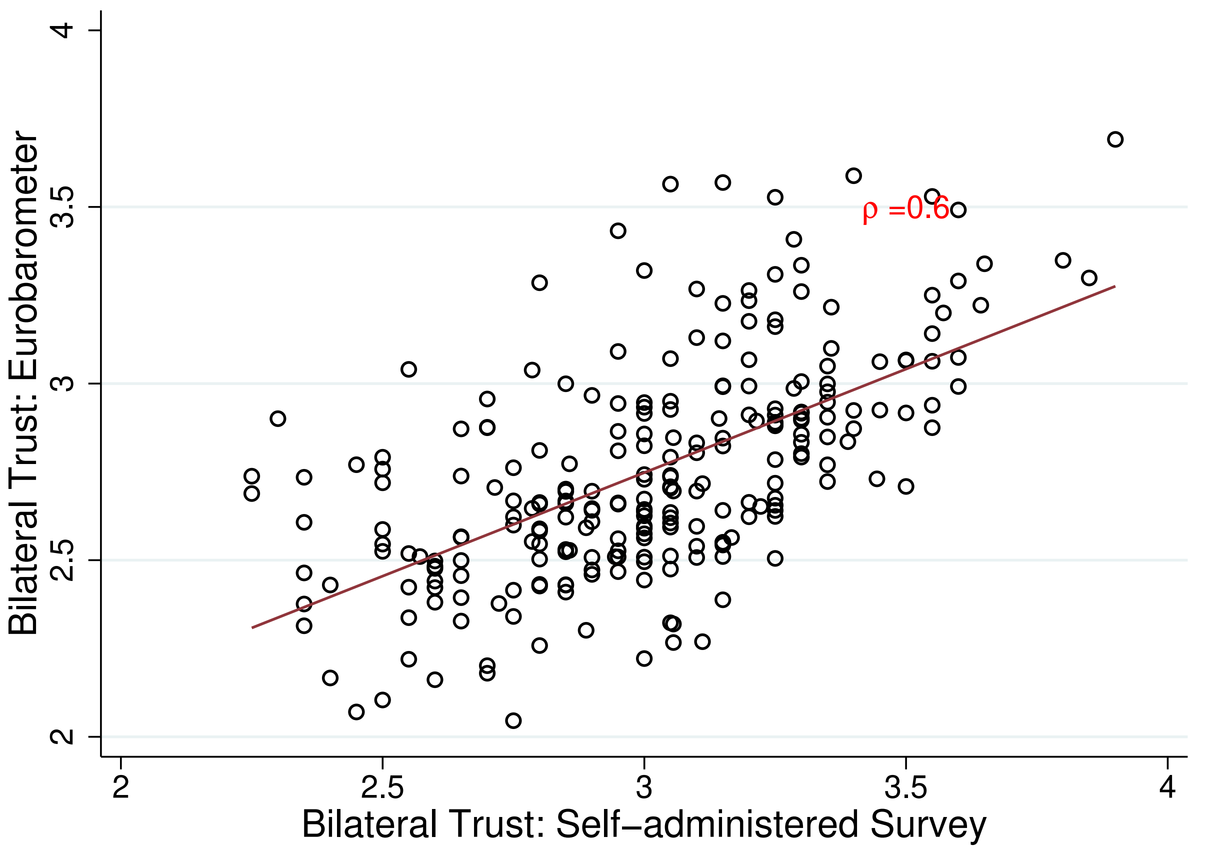


Figure F.2: Correlation between Eurobarometer Bilateral Trust and Self-administered Bilateral Trust Survey

Notes: The figure plots Eurobarometer's bilateral trust measures (averaged over the years from 1976 to 1996) and our self-administered bilateral trust measure. The unit of observation is country dyad and the correlation is shown using Stata command *binscatter*

Table F.1: Linear Estimation Predicting Preference for Foundational Skills: Using Self-Administered Survey

	OLS						IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Trust 2022	0.196	0.159	0.290	0.236	0.275	0.284		0.809
(HQ-Local)	(0.0626)	(0.0428)	(0.0579)	(0.0420)	(0.0417)	(0.0480)		(0.345)
Somatic Distacne							-0.0156	
(HQ-local)							(0.00744)	
Job Req. College		0.0156	-0.0134	0.0192	0.0124	0.0123	0.000265	0.0211
Degree		(0.0199)	(0.0311)	(0.0203)	(0.0181)	(0.0181)	(0.000829)	(0.0189)
Job Req. Graduate		0.00453	-0.00328	0.0191	0.00963	0.00971	0.000106	0.0208
Degree		(0.0168)	(0.0328)	(0.0210)	(0.0222)	(0.0222)	(0.000867)	(0.0221)
Job Req. Short-Cycle		-0.0136	-0.0393	-0.0164	-0.0177	-0.0177	-0.00109	-0.00703
Tertiary Degree		(0.0101)	(0.0147)	(0.00857)	(0.00885)	(0.00885)	(0.000798)	(0.00780)
Job Req.		0.00125	0.00528	-0.00175	0.00400	0.00385	-0.000137	0.0136
Non-Tertiary Degree		(0.0134)	(0.0200)	(0.0152)	(0.0144)	(0.0145)	(0.000816)	(0.0151)
Job Req. Work		0.00692	0.0316	0.0126	0.00738	0.00736	-0.000179	0.00657
Experience		(0.0108)	(0.0179)	(0.0113)	(0.0120)	(0.0120)	(0.000432)	(0.0133)
Num. of Skills (log)		-0.0302	-0.122	-0.0449	-0.0163	-0.0163	-0.0000787	-0.0212
		(0.0116)	(0.0148)	(0.0140)	(0.0149)	(0.0149)	(0.000179)	(0.0169)
Diff. in GDP per						0.0161	-0.0106	0.0301
Capita (log)						(0.00889)	(0.0141)	(0.0110)
Common Legal Origin						-0.000745	-0.158	0.0701
(HQ-Local)						(0.0214)	(0.0263)	(0.0617)
Physical Distance						0.0108	-0.101	0.0664
(log) (HQ-Local)						(0.0163)	(0.0220)	(0.0430)
Observations	1018327	1016130	1004098	999074	1002434	1002434	906252	906252
R^2	0.037	0.356	0.207	0.413	0.577	0.577	0.988	0.558
Fixed Effects:								
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation		Yes		Yes				
Employer			Yes	Yes				
Occupation x Employer					Yes	Yes	Yes	Yes

Standard errors in parentheses
$p < 0.05$, $p < 0.01$, $p < 0.001$

Table F.2: Bilateral Trust Matrix

	AUT	BEL	BGR	CHE	CHN	CZE	DEE	DEU	DEW	DNK	ESP	FIN	FRA	GBR	GRC	HUN
AUT	3.56	2.95		3.24		2.05		3.09		2.95	2.58	2.94	2.62	2.59	2.52	2.31
BEL	2.83	3.07	2.46	2.93	2.04	2.39	2.59	2.64	3.04	2.88	2.63	2.92	2.83	2.74	2.50	2.46
DEU	3.12	2.80	2.16	3.07	1.98	2.18	2.99	3.23	3.57	2.92	2.64	2.90	2.81	2.70	2.55	2.34
DNK	3.22	2.99	2.70	2.94	2.53	2.71	2.86	2.89	3.16	3.22	2.65	3.20	2.77	3.04	2.55	2.75
ESP	2.65	2.73	2.15	2.78	2.39	2.27	2.36	2.70	2.50	2.73	3.32	2.71	2.38	2.30	2.45	2.22
FIN	3.29	3.07		3.37		2.64		2.89		3.30	2.61	3.69	2.92	3.18	2.68	2.87
FRA	2.70	2.93	2.49	2.93	2.02	2.44	2.56	2.64	2.86	2.85	2.66	2.91	3.00	2.53	2.48	2.53
GBR	2.88	2.77	2.56	2.83	2.39	2.62	2.57	2.47	2.79	2.90	2.54	2.95	2.47	2.99	2.54	2.66
GRC	2.32	2.50	2.05	2.63	2.63	2.37	2.57	2.26	2.81	2.42	2.66	2.42	2.62	2.38	2.96	2.36
IRL	2.93	2.82	2.60	2.83	2.35	2.59	2.69	2.62	2.92	2.85	2.60	2.92	2.74	2.74	2.47	2.67
ITA	2.66	2.60	2.32	2.76	2.11	2.33	2.56	2.51	2.74	2.66	2.67	2.78	2.61	2.48	2.46	2.38
LUX	2.95	2.77	2.39	2.84	2.30	2.30	2.42	2.70	2.76	2.85	2.73	2.94	2.78	2.59	2.57	2.32
NLD	2.90	2.98	2.70	2.99	2.11	2.72	2.75	2.72	2.96	3.06	2.70	3.25	2.67	2.86	2.57	2.73
NOR		3.18						2.99		3.53	2.56		2.93	3.27	2.52	
PRT	2.13	2.66	2.47	2.78	2.35	2.16	2.57	2.44	2.84	2.66	2.59	2.18	2.90	2.66	2.41	2.17
SWE	3.53	3.23		3.50		2.88		3.13		3.57	2.86	3.49	3.04	3.43	2.88	2.87

	IRL	ITA	JPN	LUX	NLD	NOR	POL	PRT	ROU	RUS	SVK	SWE	TUR	USA	YUG
AUT	2.55	2.43	2.49	3.07	2.95	3.00	2.07	2.50		1.76	1.98	3.05	1.78	2.57	
BEL	2.70	2.46	2.47	3.07	2.79	2.91	2.50	2.57	2.52	2.17	2.17	2.99	1.89	2.71	2.58
DEU	2.51	2.42	2.63	2.92	2.87	2.99	1.94	2.50	2.07	2.09	1.98	3.06	1.95	2.78	2.29
DNK	2.90	2.53	2.82	3.04	3.10	3.50	2.76	2.64	2.65	2.44	2.51	3.41	2.22	2.84	2.71
ESP	2.56	2.59	2.59	2.72	2.85	2.79	2.32	2.51	2.23	2.29	2.27	2.84	1.94	2.29	2.23
FIN	2.92	2.51	3.05	3.06	3.14	3.48	2.59	2.67		1.90	2.53	3.35	2.13	2.86	
FRA	2.66	2.42	2.35	2.94	2.82	2.97	2.56	2.59	2.49	2.16	2.22	2.99	1.94	2.60	2.52
GBR	2.68	2.55	2.51	2.80	2.91	3.03	2.79	2.71	2.58	2.40	2.47	3.00	2.18	2.73	2.69
GRC	2.51	2.41	2.64	2.50	2.39	2.40	2.34	2.56	2.38	2.43	2.27	2.51	1.33	2.31	1.91
IRL	3.16	2.62	2.56	2.84	2.86	2.93	2.74	2.64	2.56	2.29	2.52	2.92	2.18	2.80	2.70
ITA	2.43	2.74	2.75	2.61	2.69	2.78	2.42	2.43	2.44	2.25	2.10	2.89	1.75	2.78	2.34
LUX	2.62	2.58	2.55	3.22	2.90	2.91	2.31	2.65	2.37	2.22	2.06	2.98	1.92	2.89	2.48
NLD	2.72	2.43	2.69	3.06	3.07	3.30	2.77	2.76	2.70	2.36	2.43	3.34	2.29	2.83	2.74
NOR	3.01	2.65	3.09	3.20	3.26			2.60		2.52				3.14	
PRT	2.51	2.55	2.43	2.71	2.70	2.22	2.20	3.29	2.46	2.12	1.79	2.24	2.03	2.70	2.52
SWE	3.26	2.81	3.19	3.31	3.33	3.65	2.69	2.97		2.45	2.79	3.59	2.39	3.20	

Notes: These values come from Eurobarometer surveys, averaged from 1970 to 1996. The country dyad in row x and column y refers to the country x's trust in country y.

Online Appendix Section G. Country-level Control Variables

This section discusses the construction of our country-level control variables. GDP per capita (logged), human capital index, and unemployment rate come from the World Development Indicators (WDI). The Rule of Law Index is from the World Bank's Governance Indicators; it measures "the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence" (Kaufmann, Kraay, and Mastruzzi 2006). We use the year 2010 as a benchmark; if data for 2010 is not available, the closest year is used.

The percentage of graduates from vocational programs is the 2018–2020 average calculated by Eurostat. We calculate the percentage of graduates in each country by dividing the number of graduates from vocational programs by the total number of graduates. Vocational education programs are specifically created to equip students with the expertise required for a particular occupation. These programs often include hands-on, work-related components such as apprenticeships and dual-system training. In the European Union, 10.2 million out of 21.4 million students (48 percent) were enrolled in vocational education.

Collective bargaining coverage, measured as the proportion of employees whose salary and working conditions are determined by collective agreements, is compiled by the European Trade Union Institute. There are nine countries with collective bargaining coverage at approximately 80 percent or more; they can be divided into two groups. The first group includes Sweden, Finland, and Denmark, where high collective bargaining coverage is due to high union membership. The second group includes Austria, Belgium, France, Italy, the Netherlands, and Portugal, where the high collective bargaining coverage is partly due to the legal framework for collective bargaining. For instance, in Belgium, agreements signed at the industry level are automatically applied to all employees in that industry. The reported year may vary slightly depending on the sources for each country. Across the EU countries, 60 percent of employees are covered by collective bargaining.

We also considered many other country-level variables used in previous cross-country studies, including foreign direct investment (% of GDP), women's labor force participation rate, fertility rate, percentage of population 25+ with a college degree and above, total population (logged) (from the World Development Indicators), number of international nongovernmental organization ties (Paxton, Hughes, and Reith 2015), religious diversity (from Pew Research Center), democracy score index (from Polity IV Project), colonial origin (Teorell and Hadenius 2005), latitude, legal origin (La Porta et al. 1998), percentage of the population belonging to a major religion (i.e., Christian, Muslim, Hindu, Buddhist, or Jewish) (from Pew Research Center), whether the country is an OECD member, and Schwartz's culture value, which includes embeddedness, harmony, egalitarian commitment, intellectual autonomy, affective autonomy, mastery, and hierarchy. We have included these additional control variables in various combinations and they do not substantially change our findings.

Online Appendix Section H. Does the Headquarters Influence Job Postings in Its Foreign Subsidiaries?

An important assumption of our paper is that a multinational firm's headquarters influences the job postings of its foreign subsidiaries. This influence could occur both directly and indirectly. The headquarters could shape the organizational design of its foreign subsidiaries, determining aspects such as structure, culture, and day-to-day practices. These organizational design choices could in turn shape the content of job postings. We call this the indirect influence of the headquarters and much research provides evidence of it (Roth and Nigh 1992; Jong et al. 2015; Haq, Drogendijk, and Holm 2017).

However, it is unclear to what extent the headquarters may directly influence job posting and hiring in foreign subsidiaries. To explore this question, in 2022 we surveyed 200 hiring managers from the platform Prolific. Our survey participants on average have over five years of hiring experience and are mainly from the United States, the United Kingdom, Poland, Portugal, South Africa, Canada, Mexico, and Spain. We required participants to have conducted hiring in a foreign subsidiary of a multinational firm. In the survey, we asked: "In local hiring, does your HQ ___?" and gave them a yes/no option for five scenarios: "(a) Set hiring standards and procedures, (b) Review hiring requirements, (c) Review job postings, (d) Review applications, (e) Involve in hiring decisions."

Our survey suggests that in the vast majority of cases, the headquarters sets some standards and procedures for the local recruiting process (87.5 percent) and reviews hiring requirements (83.3 percent). In more than half the cases, the headquarters reviews job postings and candidates' applications and is involved in hiring decisions (as shown in Online Appendix Figure H.1). These numbers are consistent with our qualitative interviews. Most respondents to whom we spoke suggested that the headquarters imposes some policies, criteria, and standards on local hiring. Many also mentioned that the headquarters would review job advertisements, wages, skill requirements, and the final hiring decision.

[Insert Online Appendix Figure H.1 about here]

We next empirically test for any correlation in hiring criteria between the headquarters and the local subsidiaries. Our strategy is to compare jobs posted in the same country with the same title by firms with different foreign headquarters. We want to see whether the job requirements in the headquarters can predict job requirements in its foreign subsidiaries. As discussed in the main paper, Lightcast's research team has coded all the skills (ESCO level 4) required in each job posting. We focus on the four most commonly mentioned skills: quantitative skills (e.g., data science and programming), soft skills (e.g., communication), creativity (e.g., think creatively), and problem-solving skills. Quantitative skills are quantified as a number, based on the number of hours required to learn them, and the other skills are coded as binary. For each skill, we conduct an ordinary least squares regression to predict whether a job posting requires that particular skill, while including fixed effects for job title, country, and sector and a robust set of controls such as degree and work experience requirements. Our independent variable of interest is the proportion of jobs in that firm's headquarters requiring that particular skill. If headquarters have no influence on their foreign subsidiaries' job postings, then we should not expect any association between the headquarters's skill requirements and those of the subsidiaries. However, as the Online Appendix Table H.1 shows, the association is quite strong. A 1-standard-deviation increase in the headquarters's skill requirements predicts a 0.06–0.17-standard-deviation increase in foreign subsidiaries' skill requirements, suggesting that the headquarters has a substantial influence on its foreign subsidiaries' job postings.

[Insert Online Appendix Table H.1 about here]

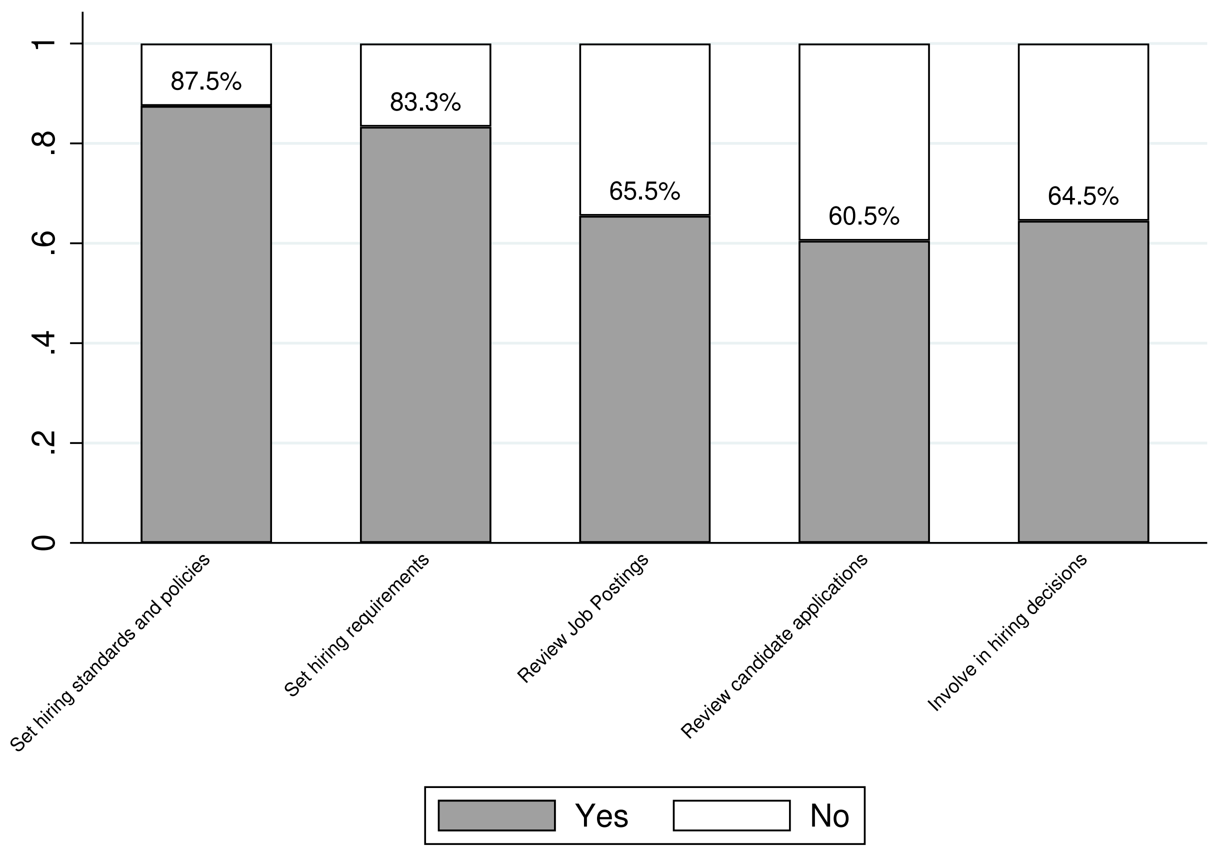


Figure H.1: Does the Headquarter Firm Influences Local Hiring?

Notes: We surveyed 200 online respondents with hiring experiences who have worked in a foreign subsidiary of a multi-national firm. Respondents were asked: “In local hiring, does your HQ ___?” and are given the “yes/no” option for the following five scenarios: (a) Set hiring standards and procedures, (b) Review hiring requirements, (c) Review job postings, (d) Review applications, (e) Involve itself in hiring decisions.

Table H.1: Linear Estimation Predicting Headquarter Effects: Evidence from Job Postings in Foreign Subsidiaries

	Technical Skills		Social Skills		Creativity Skills		Provlem Solving Skills	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Headquarter's Average Skill Level	0.0972	0.0723	0.0554	0.0546	0.201	0.191	0.137	0.102
	(0.0316)	(0.0185)	(0.0178)	(0.0148)	(0.0355)	(0.0405)	(0.0346)	(0.0330)
Job Req. College Degree	0.0953	0.129	0.0626	0.0880	0.0172	0.00637	0.0713	0.0802
	(0.0349)	(0.0434)	(0.0259)	(0.0252)	(0.0164)	(0.0158)	(0.0291)	(0.0276)
Job Req. Graduate Degree	0.0835	0.147	0.136	0.151	-0.0301	-0.0296	0.135	0.149
	(0.0396)	(0.0230)	(0.0502)	(0.0567)	(0.0232)	(0.0258)	(0.0782)	(0.0899)
Job Req. Short-Cycle Tertiary Degree	-0.0372	0.0167	0.00202	0.0155	0.00254	0.00281	-0.00874	0.000768
	(0.0306)	(0.0158)	(0.0197)	(0.0199)	(0.0103)	(0.00818)	(0.0161)	(0.0169)
Job Req. Non-Tertiary Degree	0.0130	0.0459	0.0474	0.0651	-0.00149	-0.00742	0.0551	0.0705
	(0.0332)	(0.0347)	(0.0184)	(0.0159)	(0.0117)	(0.0108)	(0.0145)	(0.0118)
Job Req. Work Experience	0.00110	0.0109	-0.0555	-0.0399	-0.00684	-0.0115	-0.0397	-0.0395
	(0.0591)	(0.0580)	(0.0115)	(0.0150)	(0.00498)	(0.00431)	(0.0146)	(0.0171)
Num of Skills Listed (log)	0.731	0.733	0.132	0.114	0.119	0.112	0.140	0.139
	(0.0245)	(0.0335)	(0.00778)	(0.00710)	(0.00775)	(0.00753)	(0.00699)	(0.0101)
Observations	215728	215728	215728	215728	215728	215728	215728	215728
R^2	0.675	0.756	0.347	0.540	0.356	0.518	0.300	0.470
Fixed Effects:								
Posting Year	Yes		Yes		Yes		Yes	
Local Country	Yes		Yes		Yes		Yes	
Occupation x Sector	Yes		Yes		Yes		Yes	
Occupation x Sector x Country x Year		Yes		Yes		Yes		Yes

Standard errors in parentheses
$p < 0.05$, $p < 0.01$, $p < 0.001$

Notes: These models examine the extent to which skill requirements in a multinational firm's headquarters country can predict skill requirements in its foreign subsidiaries. We focus on four types of commonly listed skills. Our sample includes all jobs posted by foreign subsidiaries of multinational firms; each job posting is a unit of observation. The dependent variables are binary outcomes, indicating whether or not a particular type of skill is mentioned in the posting. The independent variable, *Headquarters's Average Skill Level*, is the proportion of jobs in that firm's headquarters country that require that type of skill. Standard errors clustered at the country level are in parentheses.

Online Appendix Section I. Instrumental Variable Approach

Table 2 in the main manuscript shows results using an instrumental variable (IV) approach. Here, we discuss our IV models in greater detail.

We begin with the Hausman test, a test for endogeneity in which the null hypothesis assumes that the OLS estimates are not biased by the endogeneity of the regressor. Our result (Chi2(9) = 3881, p-value <0.001) allows us to confidently reject the null hypothesis. Specifically, we find that bilateral trust is not exogenous to employers' skill preferences, indicating that it is appropriate to use the 2SLS specification to address the issue of endogeneity.

To account for endogeneity concerns, we follow Guiso, Sapienza, and Zingales (2009) and instrument our bilateral-trust measure using somatic distance between two countries. Somatic distance captures the genetic differences between populations, generally rooted in the Neolithic Era. We believe that this measure captures the long-standing differences in two countries' cultural and genetic traits and therefore should be exogenous to hiring preferences in multinational firms today.

Low somatic distance could foster social trust, as much work has shown that people tend to trust others with similar physical characteristics and cultural values (Debruine, 2002; Delhey, Newton and Welzel, 2011). Indeed, this is an important predictor of bilateral trust and is robust after controlling for similarities in law, language, and informational overlap (Guiso, Sapienza, and Zingales 2009). Therefore, we believe that somatic distance is a valid instrument and can provide some causal evidence, especially after we include local-country and occupation-firm fixed effects.

We use somatic distance measures developed by Guiso, Sapienza, and Zingales (2009). Somatic distance is calculated by averaging the frequency of specific traits, such as height and hair color, found in the indigenous population reported by Biasutti (1954). Biasutti created a map showing the distribution of these traits across European countries. Somatic distance between two countries is then computed by adding up the absolute value of the differences in each trait.

In the first stage, we estimate the determinants of bilateral trust:

$$\begin{aligned} BTrust_{cd} = \pi_0 + \pi_1 \cdot SomaticDistance_{cd} + \pi_2 \cdot X_{jfcdy} + \pi_3 \cdot BCX_{cdy} \\ + CountryFE_c + TimeFE_y + FirmFE_f + v_{jfcdy} \end{aligned} \tag{1}$$

Next, we use this estimate to predict multinational employers' skill preferences:

$$Foundational_{jfcdy} = a \cdot BTrust_{cd} + b \cdot X_{jfcdy} + c \cdot BCX_{cdy} + CountryFE_c + TimeFE_y + FirmFE_f + u_{jfcdy} \tag{2}$$

Table 2's Model 7 reports the first-stage result and Model 8 reports the IV estimate of the effect of bilateral trust on employers' preference for foundational skills. Note that not only does bilateral trust retain its effect on employers' skill preference, but the size of its coefficient is almost twice as large as those in OLS models. This result not only reinforces our conclusions, but implies that the OLS models may have underestimated the true effect size.

One additional test of the IV model deserves mention. We want to rule out the possibility that our instruments are only weakly correlated with social trust. If this were the case, the estimate of the coefficient of the endogenous regressor—bilateral trust—would be biased. To alleviate this concern, we conduct an F-test for the null hypothesis that the coefficients of our instrument variables are zero in the first-stage regression. The resulting F-statistics (reported in the lower panel of Table 2, Model 7) comfortably pass the threshold of 10, suggesting a rather strong instrument.

Online Appendix Section J. Placebo Test: Using Bilateral Trust from Local to HQ

In this section, we include two bilateral trust measures: one from the HQ country to the local country and one from the local country to the HQ country. To give an example, when a German firm posts a job in France, our main analyses use German's trust in French as our trust measure. In this analysis, we would include both German trust in French and French trust in Germans in the model. HQ-local trust and local-HQ trust are highly correlated at the dyadic level, with a correlation of 0.8. This is perhaps not surprising since trust is often reciprocal. Because of the high correlation between the two variables, we include both variables simultaneously in the models. Based on our theory, we should expect HQ trust in the local country to matter, but not the other way around. Consistent with this expectation, Appendix Table J.1 shows that HQ-local bilateral trust strongly predicts employers' preference for foundational skills in all models, whereas local-HQ bilateral trust does not show a strong relationship with employers' skill preference.

[Insert Online Appendix Table J.1 about here]

Table J.1: Linear Estimation Predicting Preference for Foundational Skills: Evidence from Job Postings in Foreign Subsidiaries

	OLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Social Trust (HQ-Local)	0.271	0.137	0.324	0.225	0.311	0.294
	(0.0842)	(0.0537)	(0.0754)	(0.0540)	(0.0578)	(0.0509)
Social Trust (Local-HQ)	0.0232	0.0579	-0.0131	0.0289	-0.0779	0.000213
	(0.0791)	(0.0532)	(0.0686)	(0.0513)	(0.0580)	(0.0516)
Job Req. College Degree		0.0278	0.00108	0.0369	0.0327	0.0327
		(0.0221)	(0.0334)	(0.0225)	(0.0217)	(0.0217)
Job Req. Graduate Degree		0.0218	0.0121	0.0380	0.0288	0.0289
		(0.0160)	(0.0298)	(0.0187)	(0.0202)	(0.0202)
Job Req. Short-Cycle Tertiary Degree		0.0127	-0.0113	0.0132	0.0158	0.0158
		(0.0145)	(0.0249)	(0.0156)	(0.0207)	(0.0206)
Job Req. Non-Tertiary Degree		0.0196	0.0330	0.0187	0.0282	0.0278
		(0.0167)	(0.0288)	(0.0181)	(0.0200)	(0.0201)
Job Req. Work Experience		0.00108	0.0223	0.00622	-0.0000752	-0.0000815
		(0.0101)	(0.0162)	(0.0103)	(0.0100)	(0.0100)
Num. of Skills (log)		-0.0247	-0.105	-0.0324	0.00374	0.00363
		(0.0184)	(0.0259)	(0.0231)	(0.0251)	(0.0251)
Diff. in GDP per Capita (log)						0.0164
						(0.00806)
Common Legal Origin (HQ-Local)						-0.0572
						(0.0182)
Common Official Language (HQ-Local)						
Physical Distance (log) (HQ-Local)						-0.0155
						(0.0156)
Observations	1107029	1104785	1092347	1087542	1090638	1090638
R^2	0.026	0.337	0.181	0.387	0.538	0.538
Fixed Effects:						
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes	Yes	Yes
Local Country	Yes	Yes	Yes	Yes	Yes	Yes
Occupation		Yes		Yes		
Employer			Yes	Yes		
Occupation x Employer					Yes	Yes

Standard errors in parentheses

$p < 0.05$, $p < 0.01$, $p < 0.001$

Online Appendix Section K. Moderators

This section discusses the construction of our four moderators are: whether a job requires a college degree, whether it requires occupational certification, whether it requires work experience, and the required preparation level.

In constructing these variables, we use information from the job postings, LinkedIn profiles, and O*NET descriptions. College degree requirement is a binary variable: we coded a job as either requiring or not requiring at least a bachelor's degree. Of the jobs in our sample, 15 percent of jobs require at least a bachelor's degree and 85 percent require a lower degree, such as an associate degree. We only consider those jobs explicitly requiring at least a bachelor's degree as requiring a college degree and treat other jobs as not requiring a degree.

Similarly, we code a job as having a work-experience requirement if it explicitly requires any work experience, which 47 percent do. Note that many jobs may implicitly require a college degree or some work experience without explicitly saying so in the posting. For example, a firm seeking a lead engineer may assume that the degree requirement is too obvious to bother mentioning. Thus, our variables may not capture all job postings with such requirements.

We measure occupational certification requirements at the country-occupation level. Although many job postings list certification requirements, we use the certification data based on LinkedIn profiles because these are significantly easier to code. Using LinkedIn data in Europe, we measure the average number of certifications listed for each occupation in each country. In our sample, the typical job requires 0.5 certifications. Underwater diver in the United Kingdom is the occupation with the highest number of certifications (4.03); industrial and production engineer in Greece is the second-highest (3.19), and electronic engineer in Portugal is the third-highest (2.92).

Finally, we use the O*NET coding to categorize occupations into preparation levels. O*NET divides all jobs into five zones, based on the required level of education, training, and experience. The zones range from Job Zone 1, which requires little or no preparation, to Job Zone 5, which requires extensive preparation. In our sample, 8 percent of jobs are in Zone 5, 34 percent in Zone

4, 21 percent in Zone 3, 35 percent in Zone 2, and 2 percent in Zone 1.

The pairwise correlations among these four moderating variables are between -0.01 and 0.15. Given such relatively low correlations, we include these moderators in the same model. Since we have fewer valid observations for occupational certification, we also include it in a separate model. While we have already discussed the moderating effect for college degree, work experience, and job-preparation level in Table 3, here in Online Appendix Table K.1 we show the moderating effect of occupational certification. We find it consistent with our hypothesized direction: jobs requiring more certifications show less association between social trust and employers' preference for foundational skills. In both between-country and bilateral-trust models, the magnitude of the interacting terms suggests that for every additional occupational certification required, the association between trust and skill preference decrease by 20 percent in between-country models and 14 percent in bilateral-trust models.

[Insert Online Appendix Table K.1 about here]

Table K.1: Linear Estimation Predicting Preference for Foundational Skills: Moderator (Occupational Certificates)

	Local Model		Bilateral Model	
	(1)	(2)	(3)	(4)
Social Trust (Local Country)	0.351***	0.268***		
	(0.0772)	(0.0550)		
Occupational Certificates	0.0156	0.0718*	0.296**	0.331**
	(0.0203)	(0.0267)	(0.107)	(0.107)
Social Trust (Local Country)	-0.0567	-0.103		
x Occupational Certificates	(0.0644)	(0.0705)		
Social Trust (HQ-Local)			0.310***	0.336***
			(0.0652)	(0.0628)
Social Trust (HQ-Local)			-0.105*	-0.119**
x Occupational Certificates			(0.0413)	(0.0412)
Observations	10075015	10075015	808990	808990
R^2	0.573	0.573	0.536	0.536
Fixed Effects:				
Posting Year	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes
Occupation x Employer	Yes	Yes	Yes	Yes
Local Country			Yes	Yes
Country Controls		Included		Included
Job Controls	Included	Included	Included	Included

Standard errors in parentheses

$p < 0.05$, $p < 0.01$, $p < 0.001$

Notes: The table is similar to Table 4. Standard errors clustered at the country level are in parentheses.

Online Appendix Section L. Social Trust and Organizational Tenure

In this appendix section, we examine the relationship between a country's social trust and its workers' organizational tenure. Our theory suggests that in higher-trust countries, employers perceive a longer-term commitment from employees. Having no way to measure employers' perception of long-term commitment, we examine a more tangible measure: organizational tenure, or the time that a typical employee spends in an organization.

To examine organizational tenure across countries, we analyze global LinkedIn profiles. In 2023, we obtained LinkedIn profiles from data provider Revelio, which collects all public LinkedIn profiles. LinkedIn, as one of the largest social networking platforms for professionals, has self-reported career histories on over 480 million people in 233 countries. This extensive coverage makes it one of the few data sources with information on individuals' career histories across a large number of countries.

LinkedIn Sample Distribution

Although the LinkedIn data covers most countries, it has an uneven global distribution. The largest number of users come from the United States, which accounts for 24 percent of our sample. The other major economies—such as India, the United Kingdom, France, and Brazil—also have many LinkedIn users. We compare a country's representation in our LinkedIn sample to its labor-force size based on government statistics, finding that the two are moderately correlated at around 0.6. A few countries, including China, India, Japan, Ethiopia, and Indonesia, have a lower proportion of individuals using LinkedIn relative to their actual labor force. Overall, LinkedIn has a higher penetration among English-speaking countries and more-developed countries.

LinkedIn users are heavily skewed toward highly educated people. For example, 92 percent of LinkedIn users who posted educational information in the US have at least a bachelor's degree, significantly higher than the 38 percent holding at least a bachelor's degree in the US population. Consequently, LinkedIn profiles are better representations of professional and managerial workers than of blue-collar and service workers.

We also compare the demographic composition of LinkedIn users in different countries to the composition of their actual labor forces. We find that LinkedIn users' gender composition is highly representative of the actual labor force, with a correlation as high as 0.9. In comparison, LinkedIn users' age and education level in different countries are only moderately correlated with the actual labor force in those countries. Thus, the LinkedIn sample has a slightly skewed cross-country representation and the demographic compositions are moderately correlated across countries.

Analytical Strategy

As in our main analyses, we calculate a country's social trust using nationally representative surveys. In this case, given LinkedIn's global coverage, we use the World Values Survey (WVS), which covers more countries than the European Values Survey (EVS). The trust question in WVS is: "Do you think that most people can be trusted?" Respondents answer yes or no. Our measure of social trust is the proportion of respondents answering yes in each country. Despite its global coverage, the WVS covers only 104 countries. We focus on individual career data beginning in the year 2000, although the survey does extend back further, because LinkedIn's data is more comprehensive since 2000. We also exclude career histories longer than 40 years, as they are less likely to represent the formal labor market. Our final sample includes 174 million people in 104 countries.

Our analyses take place at the organization-individual level: each individual has a unique observation for every employer she has worked for. If a person changes jobs in an organization, we aggregate these experiences into one observation. Our dependent variable is simply the number of years a person spends in a given organization. The key independent variable is social trust in a given country; we include relevant individual attributes as controls, including educational attainment, immigrant status, and graduation from an elite college. We also include standard country-level control variables including GDP per capita, human capital index, rule of law, and unemployment rate. Our models also include fixed effects for the year that the person starts a career at each employer and her job title. We use her job title in the first job if she worked in multiple roles in the same organization. We do not include employer fixed effects because we have not standardized employer names across countries. All analyses use OLS regressions with clustering at the country level.

Results

Findings suggest that employees in higher-trust countries tend to stay longer in an organization than those in lower-trust countries. Online Appendix Figure L.1 shows a strong positive association between a country's social trust and its workers' organizational tenure, with a correlation as high as 0.28. Online Appendix Table L.1 uses OLS models to show the size of this relationship. In Model 1, without job-title fixed effects, a 1-standard-deviation increase in social trust predicts 1.3 more months in an organization. Model 2 includes job-title fixed effects and Model 3 includes country-level controls. In these models, a 1-standard-deviation increase in social trust is still associated with the employee spending 0.7—1.0 more months in an organization.

[Insert Online Appendix Figure L.1 about here]

[Insert Online Appendix Table L.1 about here]

Longer organizational commitment could explain why employers in higher-trust countries are more invested in candidates' potential and therefore more willing to hire based on more-foundational skills.

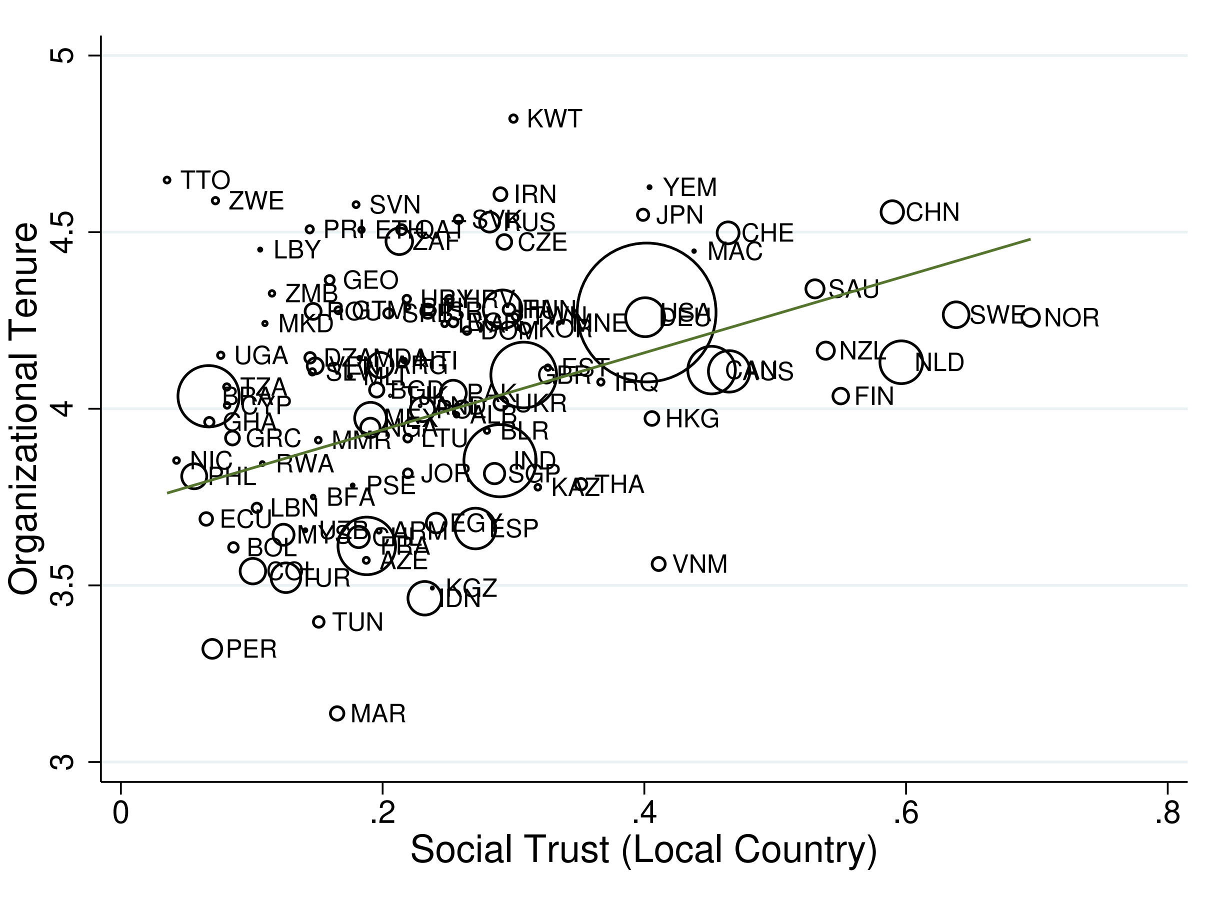


Figure L.1: Correlation between Social Trust and Organizational Tenure

Notes: The figure plots the association between social trustand organizational tenure in each country. The unit of observation is the country.

Table L.1: Linear Estimation Predicting Organizational Tenure: Evidence from LinkedIn Profiles

	All Countries		
	(1)	(2)	(3)
Social Trust (Local Country)	0.818	0.619	0.374
	(0.198)	(0.134)	(0.146)
Elite Graduating School		-0.00896	-0.00887
		(0.000884)	(0.000895)
PhD Degree		-0.199	-0.206
		(0.0289)	(0.0316)
Master's Degree		-0.254	-0.253
		(0.0138)	(0.0134)
Bachelor's Degree		-0.160	-0.161
		(0.00918)	(0.00860)
Immigrant		-0.0586	-0.0640
		(0.0117)	(0.00751)
GDP per Capita (Local Country)			0.00752
			(0.00905)
Human Capital Index (Local Country)			-0.201
			(0.216)
Unemployment Rate (Local Country)			-0.00263
			(0.00392)
Rule of Law (Local Country)			0.0611
			(0.0300)
Observations	516869877	515470700	511404089
R^2	0.142	0.406	0.406
Fixed Effects:			
Starting Year	Yes	Yes	Yes
Occupation		Yes	Yes

Standard errors in parentheses

$p < 0.05$, $p < 0.01$, $p < 0.001$

Notes: The table examines the association between social trust and employees' organizational tenure. Individual-level data come from LinkedIn. Standard errors clustered at the country level are in parentheses.

Online Appendix Section M. Social Trust and Role Flexibility

In this appendix section, we examine whether employees in higher-trust countries are given more role flexibility at their jobs. Our theory suggests that social trust leads to more role flexibility and that employees with stronger foundational skills are better able to adapt to a variety of roles. We use the European Skills and Job Survey (ESJS) to compare the degree to which employees have flexible job roles in each country.

ESJS is a survey of representative samples of adult employees (aged 25–65) in the 28 member states of the European Union. The survey collects individuals' qualifications and skills to examine the match between their skills and the skills needed in their jobs. We obtained the first and only published wave of the survey, conducted in Spring 2014, which includes a total of 48,676 adult employees in the 28 EU countries. The median country, Hungary, has 1,500 respondents, with Cyprus, Malta, and Luxembourg having the fewest at 500 and Poland having the most at 4,017.

Question Q8 in the ESJS survey could indicate employees' role flexibility: "Have any of the following changes in your role taken place?" There are six non-exclusive yes/no options: (1) "I have been promoted to a higher-level position"; (2) "I moved to a different unit/department"; (3) "I have not been promoted or moved department but the nature of my tasks and responsibilities has changed"; (4) "I now have a lower-level position than when I started"; (5) "No changes, my role has remained the same"; and (6) "Do not know." Options 2 and 3 are especially relevant. Option (2) indicates whether the employee has officially changed her unit in the organization and option (3) suggests that the employee has changed her roles and responsibilities on the job while remaining in the same position. In comparison, options 1 and 4 reflect promotion and demotion, which are associated more with the employee's rank than with her role. We also run option (5), which could reflect no role change, on a more-aggregate level.

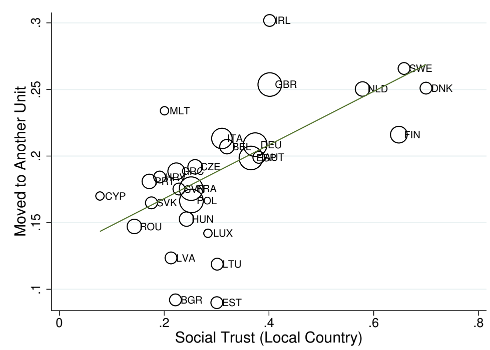
We run individual-level OLS regressions clustered at the country level to predict these three outcomes (options 2, 3, and 5). Our key independent variable is a country's social trust. We include occupation and industry fixed effects across all models to compare respondents with similar occupational and industry backgrounds.

We control for individual attributes, such as the respondent's age, gender, educational attainment, and number of years working for the current employer. Consistent with our main models, we also include relevant country-level control variables, including logged GDP per capita, rule of law, collective bargaining coverage, unemployment rate, and the percentage of graduates from vocational programs.

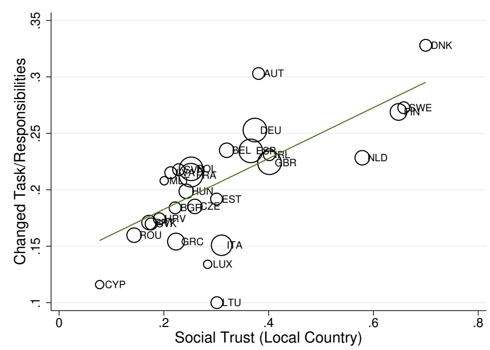
Results suggest that employees in higher-trust countries are much more likely to experience role changes than those in lower-trust countries. Online Appendix Figure M.1 shows the descriptive relationship between a country's social trust and its employees' likelihood of changing roles, finding a generally positive association. Online Appendix Table M.1 shows results from the OLS analyses. Controlling for occupation and individual characteristics, we find that those in higher-trust countries are three-percent more likely than those in lower-trust countries to move into a different unit of the same employer, four-percent more likely to change tasks and responsibilities without changing job title, and five-percent less likely to have no role change at all. These findings are consistent with our proposition that social trust is associated with more role flexibility for employees.

[Insert Online Appendix Figure M.1 about here]

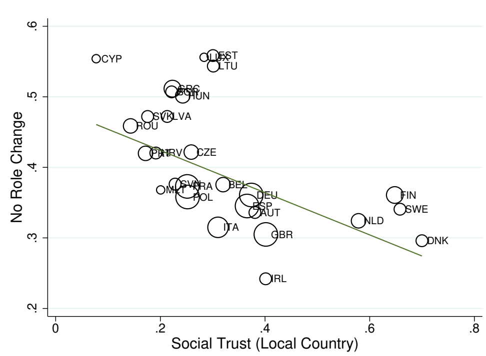
[Insert Online Appendix Table M.1 about here]



(a) Moved to Another Unit



(b) Changed Tasks/Responsibilities



(c) No Role Change

Figure M.1: Association between Social Trust and Role Flexibility

Notes: The figures descriptively show the association between a country's social trust and its employee role flexibility. Information on employee role flexibility comes from the European Skills and Jobs Survey, conducted in 2014 in 28 EU countries and include 48,676 respondents. In Figures a-c, respondents are asked "Have any of the following changes in your role taken place?" (a) "I moved to a different unit/department" (b) "I have not been promoted or moved department but the nature of my tasks and responsibilities have changed" (c) "No changes, my role has remained the same".

Table M.1: Linear Estimation Predicting Employees Jobs' Role Flexibility: Evidence from ESJS Survey

	Moved to Another Unit		Changed Task/Responsibilities		No Role Change	
	(1)	(2)	(3)	(4)	(5)	(6)
Social Trust (Local Country)	0.194	0.200	0.234	0.162	-0.308	-0.383
	(0.0403)	(0.0505)	(0.0300)	(0.0566)	(0.0682)	(0.0909)
Age	-0.0490	-0.0494	-0.0139	-0.0145	0.104	0.105
	(0.00472)	(0.00489)	(0.00514)	(0.00524)	(0.00544)	(0.00521)
Gender	-0.00443	-0.00335	0.0110	0.00846	0.0301	0.0292
	(0.00428)	(0.00424)	(0.00619)	(0.00407)	(0.00790)	(0.00689)
Years in Job	0.0101	0.0103	-0.00115	-0.00119	-0.0169	-0.0170
	(0.000534)	(0.000571)	(0.000475)	(0.000449)	(0.000399)	(0.000392)
College Degree	0.0388	0.0427	0.0559	0.0603	-0.0748	-0.0780
	(0.0481)	(0.0458)	(0.0554)	(0.0565)	(0.0765)	(0.0755)
Graduate Degree	0.0228	0.0345	0.0560	0.0521	-0.113	-0.119
	(0.0513)	(0.0502)	(0.0592)	(0.0598)	(0.0662)	(0.0693)
Short-cycle Tertiary Degree	0.0254	0.0321	0.0518	0.0550	-0.0431	-0.0486
	(0.0492)	(0.0464)	(0.0565)	(0.0580)	(0.0771)	(0.0761)
Non-Tertiary Degree	0.0178	0.0200	0.0404	0.0436	-0.0198	-0.0187
	(0.0482)	(0.0460)	(0.0568)	(0.0571)	(0.0795)	(0.0798)
GDP per Capita (log) (Local Country)		0.0394		-0.0222		-0.0261
		(0.0190)		(0.0194)		(0.0368)
Unemployment Rate (Local Country)		-0.289		-0.153		0.720
		(0.131)		(0.214)		(0.500)
% of Graduates from Vocational Education (Local Country)		-0.0303		-0.0110		0.0395
		(0.0418)		(0.0424)		(0.0737)
Rule of Law (Local Country)		-0.0229		0.0368		0.0497
		(0.0133)		(0.0282)		(0.0294)
Collective Bargining Coverage (Local Country)		-0.0548		0.0266		-0.000177
		(0.0296)		(0.0231)		(0.0598)
Observations	48306	48306	48306	48306	48306	48306
R^2	0.070	0.072	0.015	0.017	0.129	0.131
Fixed Effects:						
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

$p < 0.05$, $p < 0.01$, $p < 0.001$

Notes: The table examines the association between social trust and role flexibility. Individual-level data come from the European Skills and Jobs Survey. Standard errors clustered at the country level are in parentheses.

Online Appendix Section N. Evidence on Employee Training

In this appendix section, we examine whether employees in higher trust countries receive more employer training. According to our theory, employers in higher-trust societies prefer more foundational skills because they expect to train employees more. We use the European Skills and Job Survey (described above) to compare the degree to which employers in each country provide job training. While the survey cannot causally pinpoint our mechanisms, it could provide some suggestive evidence supporting our story.

Two survey questions are particularly relevant for our purpose. The first (Q33) is: "In the last 12 months, have you undergone any of the following types of training for your current job? (1) Training courses attended mostly or only during work hours; (2) Training courses attended mostly or only outside of work hours; (3) Training while performing your regular job; (4) I have not undergone any training." These four answer choices are not mutually exclusive; respondents are asked to select all that apply. We use this question because it not only indicates whether employees have received any training (Q33.4), but also the source of this training. According to our theory, workers in higher-trust countries should receive more training opportunities at work.

The second question (Q34) is: "Who paid for this training? (1) You paid; (2) Your employer paid; (3) Your employer paid part of the cost; (4) The government or other public sector organization paid; (5) Someone else/another organization paid." We combine the second ("Your employer paid") and the third ("Your employer paid part of the cost") options to indicate that the respondent's employer at least partially paid for training. Our theory predicts that employers in higher-trust countries are more likely to do so.

We conduct individual-level OLS regressions to predict outcomes related to these two questions. Our key independent variable is social trust in the country. Since this variable is at the country level, we use country-level clustering in all our models. To make sure we are comparing respondents with similar occupational and industry backgrounds, we include occupation and industry fixed effects across all models.

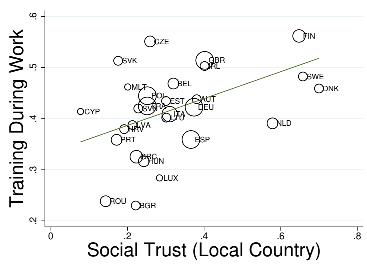
We include relevant individual-level control variables, including the respondent's age, gender, educational attainment, and number of years working for the current employer. Consistent with our main model, we also include country-level controls—including logged GDP per capita, unemployment rate, and the number of ties to international organizations—to control for a country's economic and social development, which might be associated with trust and employee training at work.

Online Appendix Figures N.1 show the association between a country's social trust and its employee training. A country's social trust positively predicts the likelihood of employees receiving on-the-job training (Figure a) and of employers paying for the training (Figure e). It negatively predicts the likelihood of attending training outside work (Figure b) and of receiving no training at all (Figure e). These associations are consistent with our theoretical prediction that employees in higher-trust countries receive more employer-sponsored training.

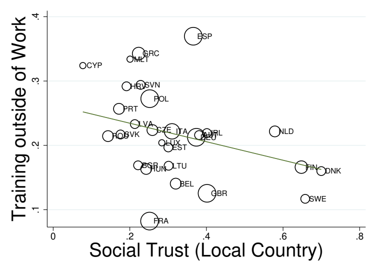
[Insert Online Appendix Figure N.1 about here]

Online Appendix Table N.1 runs these associations using OLS models. First, we find that employees in higher-trust countries are indeed more likely to receive training from their employers. Moving from a low-trust country (Cyprus) to a high-trust country (Denmark), employees are 15.6 percentage points more likely to receive training during work hours (Model 1), 11.4 percentage points less likely to attend training outside work (Model 3), and 22.4 percentage points more likely to have employers paying for their training. These effect sizes decline after including country-level controls and become statistically insignificant in some models. Our country-level controls are highly correlated with social trust; hence it is unclear whether the associations we observe are due to social trust or to some other country characteristics. Nevertheless, these analyses provide another data point on potential mechanisms underlying our theory.

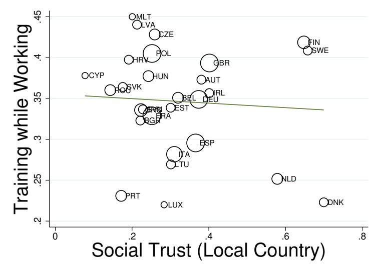
[Insert Online Appendix Table N.1 about here]



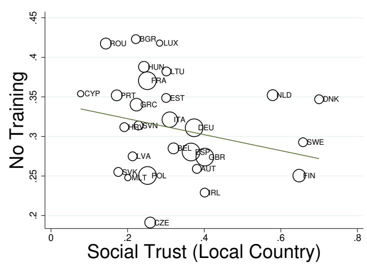
(a) Training during Work



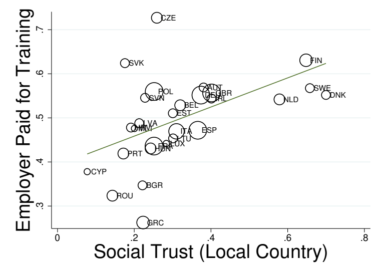
(b) Training outside of Work



(c) Training while Working



(d) No Training



(e) Employer-paid Training

Figure N.1: Association between Social Trust and Employee Training

Notes: The figures descriptive show the association between a country's social trust and its employee training. Information on employee training comes from the European Skills and Jobs Survey, conducted in 2014 in 28 EU countries and include 48,676 respondents. In Figures a-d, respondents are asked "In the last 12 months, have you undergone any of the following types of training for your current job" and asked to select among (a) "Training courses attended mostly or only during work hours" (b) "Training courses attended mostly or only outside of work hours" (c) "Training while performing your regular job" (d) "I have not undergone any training". In Figure (e), respondents are asked "Who paid for this training?" and could choose from employers or other sources.

Table N.1: Linear Estimation Predicting Employees' Training: Evidence from ESJS Survey

	During Work		Outside Work		While Working		No Training		Employer Paid	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Social Trust (Local Country)	0.248	0.111	-0.182	-0.0544	-0.0244	-0.00902	-0.0762	-0.0562	0.413	0.254
	(0.0901)	(0.131)	(0.0762)	(0.131)	(0.0975)	(0.129)	(0.0713)	(0.102)	(0.0906)	(0.0831)
Age	-0.0299	-0.0311	-0.0163	-0.0147	-0.0285	-0.0311	0.0439	0.0446	-0.000326	-0.00475
	(0.00460)	(0.00468)	(0.00588)	(0.00428)	(0.00642)	(0.00633)	(0.00588)	(0.00539)	(0.00480)	(0.00479)
Gender	-0.0194	-0.0219	-0.00254	0.000655	0.0193	0.0139	0.0145	0.0158	-0.0276	-0.0346
	(0.00632)	(0.00593)	(0.00504)	(0.00508)	(0.00690)	(0.00577)	(0.00636)	(0.00597)	(0.00709)	(0.00719)
Years in Job	0.00437	0.00455	0.000505	0.000635	-0.00109	-0.000616	-0.00188	-0.00214	0.00361	0.00385
	(0.000442)	(0.000388)	(0.000444)	(0.000333)	(0.000395)	(0.000310)	(0.000377)	(0.000356)	(0.000472)	(0.000464)
College Degree	0.235	0.250	0.0856	0.0687	0.141	0.140	-0.00297	-0.00504	0.270	0.289
	(0.0766)	(0.0760)	(0.0493)	(0.0464)	(0.0582)	(0.0594)	(0.0971)	(0.0951)	(0.110)	(0.108)
Graduate Degree	0.239	0.256	0.0269	0.0318	0.142	0.158	0.0196	0.00383	0.266	0.277
	(0.0717)	(0.0745)	(0.0626)	(0.0557)	(0.0583)	(0.0621)	(0.0846)	(0.0911)	(0.108)	(0.108)
Short-cycle Tertiary Degree	0.199	0.218	0.0849	0.0682	0.120	0.120	0.0195	0.0147	0.282	0.303
	(0.0733)	(0.0742)	(0.0550)	(0.0510)	(0.0560)	(0.0580)	(0.101)	(0.0979)	(0.108)	(0.106)
Non-Tertiary Degree	0.189	0.196	0.0204	0.00843	0.123	0.121	0.0581	0.0603	0.287	0.286
	(0.0750)	(0.0745)	(0.0465)	(0.0451)	(0.0589)	(0.0588)	(0.0980)	(0.0973)	(0.113)	(0.111)
GDP per Capita (log) (Local Country)		0.0341		0.00205		-0.0262		-0.0149		-0.00664
		(0.0414)		(0.0328)		(0.0278)		(0.0335)		(0.0358)
Unemployment Rate (Local Country)		-0.447		1.202		-0.153		-0.141		-1.090
		(0.296)		(0.667)		(0.254)		(0.454)		(0.456)
% of Graduates from Vocational Education (Local Country)		0.117		0.194		0.0933		-0.184		0.232
		(0.112)		(0.0947)		(0.0943)		(0.0868)		(0.0881)
Rule of Law (Local Country)		0.0288		-0.0297		0.0323		-0.00818		0.0502
		(0.0272)		(0.0348)		(0.0254)		(0.0264)		(0.0264)
Collective Bargining Coverage (Local Country)		-0.0770		-0.0695		-0.0709		0.0831		-0.00879
		(0.0548)		(0.0692)		(0.0435)		(0.0471)		(0.0559)
Observations	48306	48306	48306	48306	48306	48306	48306	48306	33038	33038
R^2	0.053	0.058	0.058	0.071	0.018	0.021	0.056	0.059	0.048	0.071
Fixed Effects:										
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$p < 0.05$, $p < 0.01$, $p < 0.001$

Notes: The table examines the association between social trust and employee training in a country. Individual-level data come from the European Skills and Jobs Survey. Standard errors clustered at the country level are in parentheses.

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