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

Online Appendix Section A. Matching Lightcast with Orbis to Identify Multi-National Firms

An important step in our data cleaning is to identify multi-national organizations and their headquarters. To do so, we merge our Lightcast European job postings with the Orbis database. The Orbis database 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 includes both public and private firms, detailed information on firms' 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 ten employees in the European Union countries, which reduces the pool of available firms in Orbis to 1.6 million. Our assumption is that firms with fewer than ten employees are unlikely to be multi-national employers. Since the purpose of merging with Orbis is to determine the headquarter country of multi-national firms, we impose this employee number cutoff and focus our resources on a smaller sample to ensure accurate matching.

Our matching is based on employer name, industry, and country location. After collecting a job posting, Lightcast's research team uses proprietary algorithms to identify the posting's employer name, industry (NACE level 2), and location (country and local region). In the first step, we standardize the Lightcast employer names by removing the common company suffixes such as "Inc", "Ltd," and "Gmbh." We then simply matched employer names in Lightcast and Orbis and identified those with the same standardized name, industry code, and country. The country name is the country where the job is posted. Since the Orbis database includes separate entries for each foreign subsidiary of a multi-national organization, we can match the job postings to specific foreign subsidiaries. Out of the 60 million job postings, 12.8 million can be matched exactly based on these criteria.

In the next step, we relax the criteria for exact standardized employer name, since employer name could be spelled differently (e.g., *GVF VersicherungsMakler AG* versus *GVF Versicherungs-Makler 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 the correctly matched pair. There are 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 Orbis employer name, sorted by similarity score. This leaves a sample of 162,258 such pairs. We, with the help of two research assistants, 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 had a high level of certainty.

Online Appendix Section B. 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 Figure Online Appendix B.1 for examples). Lightcast's skill coding is based on ESCO level 3 skills, a widely used skill categorization system 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, the Lightcast's research team then tries to assess whether each of these skills is mentioned in a job posting.

[Insert Figure Online Appendix B.1 about here]

Lightcast's ontology team focusing on European job postings is composed of more than 30 experts, including HR specialists, academics, and government ministers. More than half of them have a PhD degree and five are full time Lightcast employees. There is at least one native speaker for each language present 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 and keywords including numerous neighborhood and negation rules. The extensive set of rules allows the team to distinguish skills with similar words, such as between *model* as in a business plan and *model* as it refers to a software development tool.

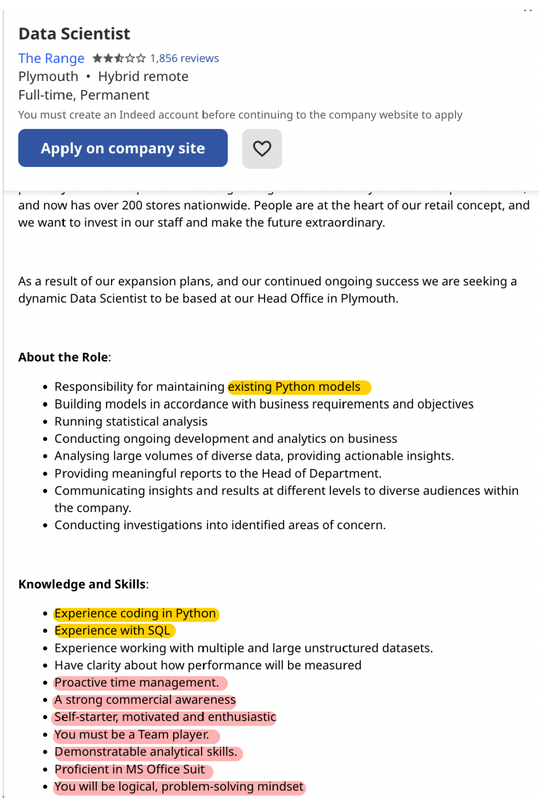
Using this method, the Lightcast team identifies all the ESCO skills required in each job posting. The median job posting lists seven required skills; 17 percent list zero skills and 47 percent require more than 10 skills. Some countries tend to list more skills, such as Ireland, the United Kingdom and Luxembourg, with an average number of listed skills above 20; whereas some countries tend to list fewer skills, such as Slovenia, Finland, Croatia and Estonia with an average number of listed skills below five.

To validate Lightcast 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). The O*NET system was developed by the US Bureau of Labor Statistics. It was first published in 1998 and has been continuously updated. O*NET provides information for around 1000 SOC occupations and for each occupation, it rates the occupation across 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 different skill categories, and we manually coded all the ESCO skills to match relevant ESCO skills 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 broad O*NET skill categories. In the end, we identify 15 broad skill categories that have a 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 15 broad skill 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.

Figure Online Appendix B.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 skills and complex problem solving skills, 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 levels of correlation 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 different skill categorizations.

[Insert Figure Online Appendix B.2 about here]



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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.

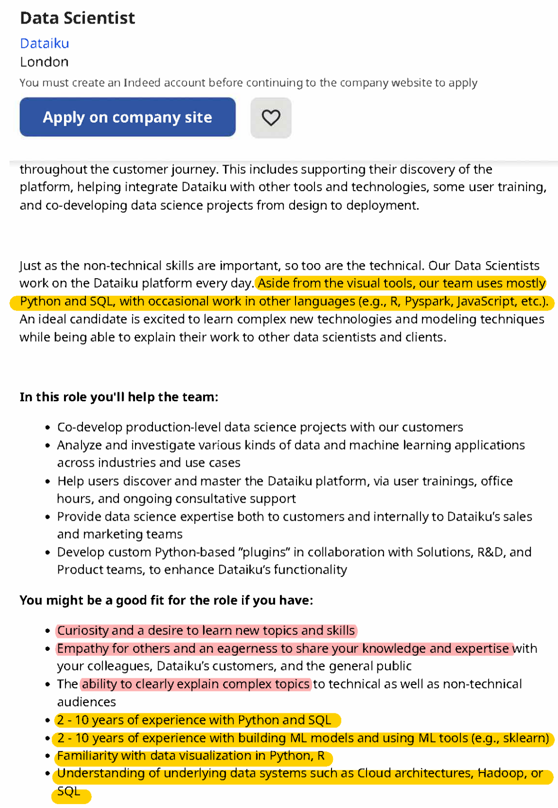
About the Role:

- 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



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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 Online Appendix B.1: Examples of Job Postings

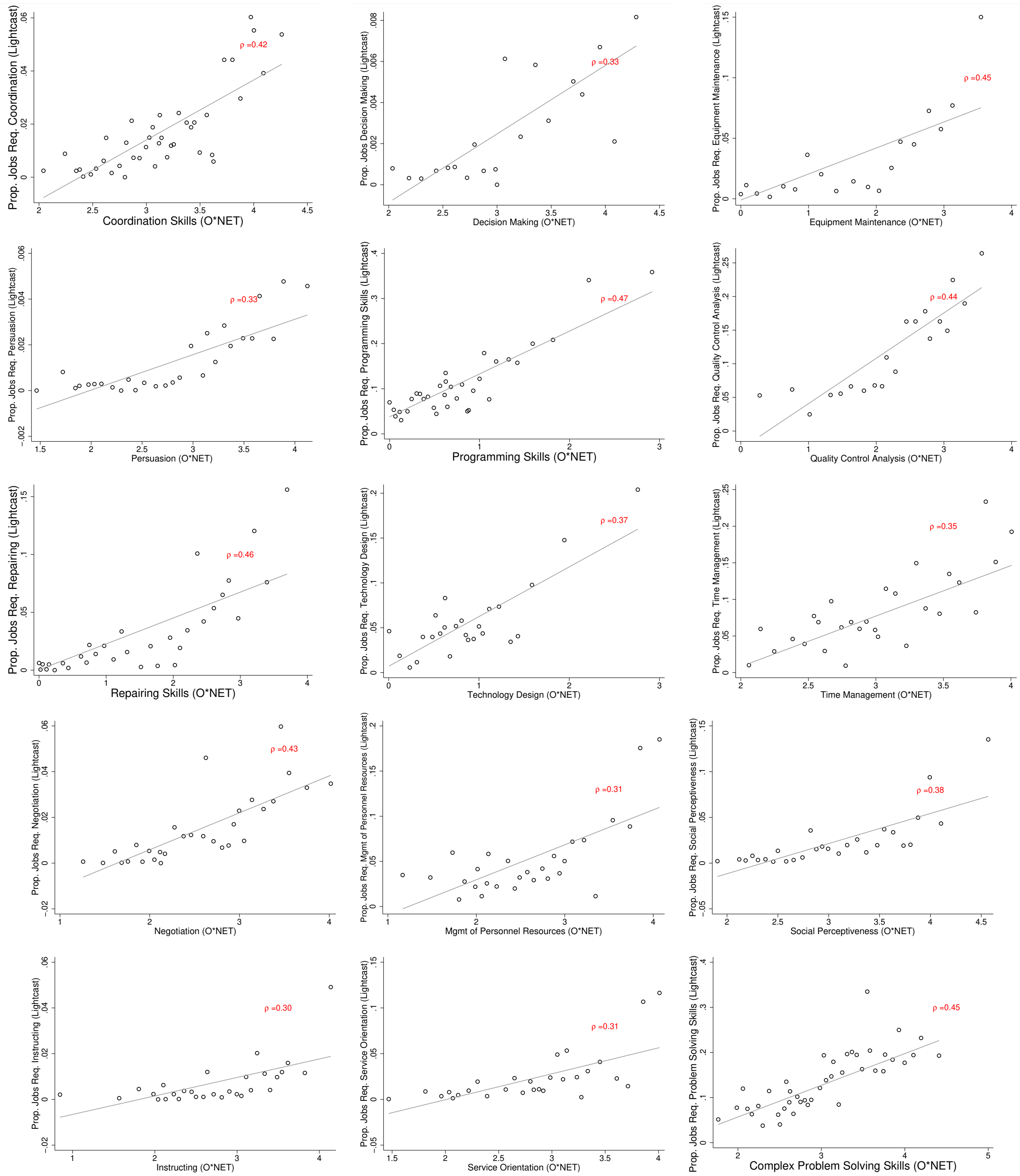
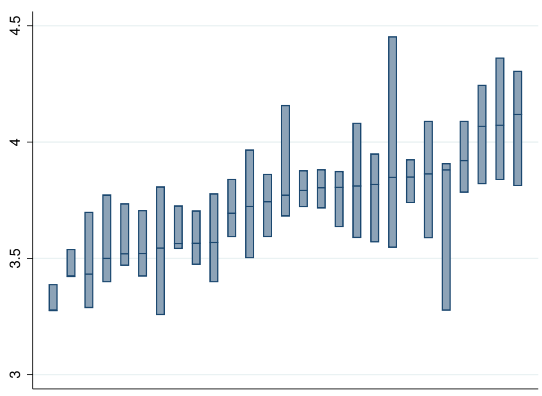
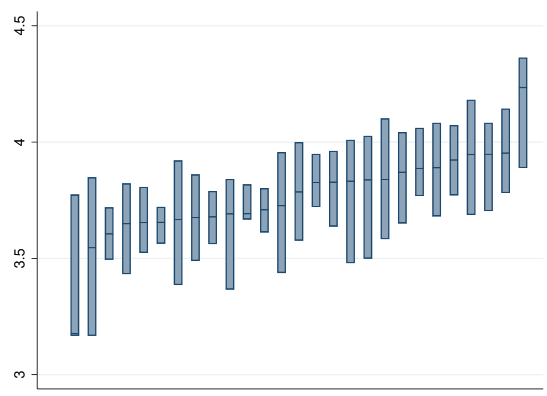


Figure Online Appendix B.2: Comparing Lightcast Skills and O*NET ratings

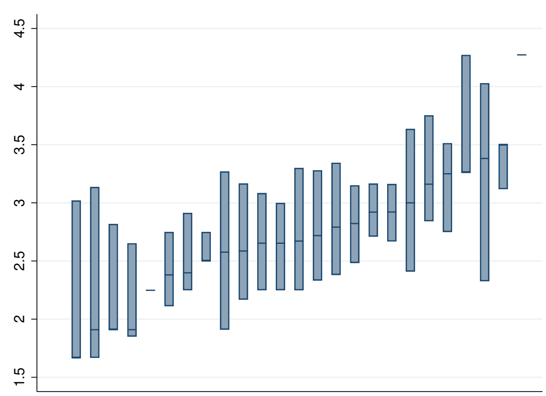
Notes: The figures show employers' preference for foundational vs. advanced skills for (a). shop sales assistant; (b). executive secretaries; (c) electrical mechanics across 28 EU countries. Employers' skill preference is at the job posting level. For each job posting, Lightcast parses the skills listed. We conduct surveys to measure where each skill sits on the foundational vs. advanced scale and take the average value across all skills in a job 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 job lists foundational instead of advanced skills.



(a) Shop Sales Assistant



(b) Executive secretaries



(c) Electrical mechanics

Figure Online Appendix B.3: Skill Preference by Occupation

Notes: The figures show employers' preference for foundational vs. advanced skills for (a). shop sales assistant; (b). executive secretaries; (c) electrical mechanics across 28 EU countries. Employers' skill preference is at the job posting level. For each job posting, Lightcast parses the skills listed. We conduct surveys to measure where each skill sits on the foundational vs. advanced scale and take the average value across all skills in a job 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 job list foundational instead of advanced skills.

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

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 high collective bargaining coverage at approximately 80 percent or more, and 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, Netherlands, and Portugal. The high collective bargaining coverage in these countries 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 of each country. Across the EU countries, 60 percent of employees are covered by collective bargaining.

We have also considered many other country-level variables that have been 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 non-governmental organization ties (from Paxton Hughes and Reith 2015), religion diversity (from Pew Research Center), democracy score index (from Polity IV Project), colonial origin (from Teorell and Hadenius 2005), latitude, legal origin (from La Porta et al., 1998), Schwartz's culture value, which includes embeddedness, harmony, egalitarian commitment, intellectual autonomy, affective autonomy, mastery and hierarchy, percentage of the population belonging to major religions, including Christian, Muslim, Hindu, Buddhist, and Jewish (from Pew Research Center), and whether the country is currently a member of the OECD. We have included these additional control variables in various combinations, and they do not substantially change our findings.

Online Appendix Section D. Instrument Variable Approach

Table 2 in the main manuscript briefly discusses results using an instrumental variable (IV) approach. In this Appendix, 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 across populations, generally rooted back to 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 multi-national firms today.

At the same time, somatic distance could foster social trust, as much work has shown that people tend to trust others who share similar physical characteristics and cultural values (Debruine, 2002; Delhey, Newton and Welzel, 2011). Indeed, past work shows that 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 (hair color, height, etc.) 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 multi-national 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 instrumental variable estimate of the effect of bilateral trust on employers' preference for foundational skills. It is worth noting that not only does the 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 a mention. We want to rule out the possibility that our instruments are only weakly correlated with social trust. If this is 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 E. Heckman Model for Selection

In this appendix, we use the Heckman model to address the selection concern with multi-national firms' job postings. A multi-national firm's decision to enter a given foreign market may be associated with that firm's social trust, which could introduce possible selection issues. To address this concern, we employ Heckman's (1976) widely used two-step approach to correct multinational firms' endogenous location choice. In the first step, we run a probit model to estimate the probability that a multi-national firm posts any job in a foreign country. From this, we calculate the Mills ratio, designed to correct sample selection concerns in OLS estimates.

However, before showing the Heckman model, we first examine how much social trust is associated with multi-national firms' decisions to post jobs in a particular country. If social trust strongly predicts a firm's decision to post in a particular country, then selection could be a major issue for our analyses. However, if social trust is not significantly associated with the number of job postings, then we should be less concerned with selection issues in the first place.

Table Online Appendix E.1 shows how bilateral trust predicts the presence of job postings in foreign subsidiaries. The unit of analysis is the year and country-to-country dyad. The dependent variables are (1) whether firms headquartered in country A have posted any job in country B in each year, and (2) the logged number of jobs that firms headquartered in country A have posted in country B in each year. All models include year-fixed effect and bilateral controls, including differences in logged GDP per capita, logged physical distance, whether countries have a common legal origin, and whether they share the same official language. These bilateral controls help account for physical distances and economic differences between two countries that could simultaneously influence between-country trust and multi-national firms' decision to hire in the country. As the table shows, social trust has little association with both dependent variables. The coefficients are quite small and statistically insignificant. Among the control variables, physical distances between two countries have a negative and significant effect on multinational firms' decision to post jobs in a foreign market. These results suggest that social trust is not strongly associated with the presence of job postings in foreign subsidiaries, which should alleviate the selection concern.

[Insert Table Online Appendix E.1 about here]

Nevertheless, we still conduct a Heckman selection model in Table Online Appendix E.2. In all model specifications and in both step one and step two, the full list of control variables of Table 2 are included. We present some on the first step, and more detail on the second step of the estimation, not all coefficients are reported to save space. In all specifications, we follow Keller and Yeaple (2013) and include two exclusion variables: (1) A country's Foreign Market Potential estimated by *The Economists*; (2) A country's rank in World Bank's Ease of Doing Business Index. A multinational firm's decision to enter a foreign market is dependent on both the country's market potential, including its market size, market growth rate, and economic freedom, and its cost of starting a business, such as getting permits, accessing credits, and paying taxes. At the same time, both market potential and fixed costs are independent of employers' skill preferences, these measures can thus plausibly serve as exclusion restrictions. Consistent with this intuition, both Foreign Market Potential and Ease of Doing Business are positively associated with a multi-national firm's likelihood of posting jobs in a particular country.

[Insert Table Online Appendix E.2 about here]

In column (1), we use the Stata command *heckman* to fits the two-step regression models automatically. However, as *heckman* command does not allow for clustered standard errors, in Models 2-6, we calculate the Mills ratio manually and include the ratio in the second-stage models. Model 2 replicated the result in Model 1. Consistent with Table 2, we add increasingly stricter model specifications from Model 2 to Model 6. Model 2 uses country-fixed effects and job-level covariates as controls; model 3 adds occupation-fixed effects; model 4 takes out occupation-fixed effects and adds in employer-fixed effects instead; model 5 uses occupation-employer dyadic fixed effects; and model 6 adds country-level covariates as controls. In these models using Heckman selection, the effect size of social trust on employers' skill preferences is similar to that using OLS estimates in Table 2: in both cases the coefficients range from 0.20-0.29, depending on model specifications. These results suggest that sample selection does not strongly bias our estimates in

Table 2.

Table Online Appendix E.1: Linear Estimation Predicting Whether a Job Has Been Posted between Two Countries: Does Social Trust Matter

	Posting Jobs		Num of Jobs Posted	
	(1)	(2)	(3)	(4)
Social Trust	-0.00918	0.133	-0.392	0.0946
(HQ-Local)	(0.147)	(0.0720)	(0.659)	(0.370)
Common Official	-0.301	-0.0879*	1.409*	0.720*
Language (HQ-Local)	(0.153)	(0.0409)	(0.511)	(0.309)
Physical Distance	-0.366***	-0.223***	-1.589***	-2.027***
(log) (HQ-Local)	(0.0190)	(0.0387)	(0.320)	(0.210)
Diff. GDP per Capita	-0.108**	-0.00673	-0.446*	-0.182
(log) (HQ-Local)	(0.0343)	(0.0125)	(0.164)	(0.0925)
Common Legal Origin	-0.217	-0.0450	-2.035*	-1.341
(HQ-Local)	(0.167)	(0.0646)	(0.767)	(0.652)
Observations	1552	1552	936	936
R^2	0.373	0.682	0.271	0.562
Fixed Effects:				
Posting Year	Yes	Yes	Yes	Yes
Local Country		Yes		Yes

Standard errors in parentheses

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

Table Online Appendix E.2: Heckman Model Predicting Preference for Foundational Skills: Evidence from Job Postings in Foreign Subsidiaries

	Heckman	2 Steps				
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
Social Trust	0.241***	0.241***	0.195***	0.291***	0.224***	0.214***
(HQ-Local)	(0.00478)	(0.0482)	(0.0320)	(0.0431)	(0.0421)	(0.0438)
Job Req. College	0.00406	0.00406	0.0484	0.0517	0.0566*	0.0567*
Degree	(0.00803)	(0.0370)	(0.0271)	(0.0367)	(0.0275)	(0.0275)
Job Req. Graduate	0.000778	0.000778	0.0302	0.0586	0.0484	0.0486
Degree	(0.00806)	(0.0352)	(0.0237)	(0.0339)	(0.0268)	(0.0267)
Job Req. Short-Cycle	0.0233**	0.0233	0.0259	0.0375	0.0363	0.0364
Tertiary Degree	(0.00788)	(0.0361)	(0.0245)	(0.0348)	(0.0287)	(0.0287)
Job Req.	0.0757***	0.0757*	0.0345	0.0790*	0.0509	0.0508
Non-Tertiary Degree	(0.00793)	(0.0382)	(0.0257)	(0.0377)	(0.0282)	(0.0282)
Job Req. Work	0.00520***	0.00520	0.00239	0.00555	0.000895	0.000896
Experience	(0.000167)	(0.00280)	(0.00182)	(0.00306)	(0.00238)	(0.00238)
Num. of Skills (log)	-0.107***	-0.107***	-0.0152	-0.101***	0.00773	0.00767
	(0.000574)	(0.0212)	(0.0173)	(0.0243)	(0.0242)	(0.0242)
Diff. in GDP per						0.0103
Capital (log) (HQ-Local)						(0.00765)
Common Legal Origin						-0.0227
(HQ-Local)						(0.0200)
Physical Distance						-0.00290
(log) (HQ-Local)						(0.0171)
Mills Ratio: λ		0.486*	0.140	0.459**	0.258*	0.223
		(0.155)	(0.112)	(0.141)	(0.124)	(0.131)
Selection Stage						
Market Power Score	0.0979***					
	(0.000373)					
Ease of Doing	0.0193***					
Business Rank	(0.0000961)					
Observations	1388828	1146658	1144925	1146658	1144925	1144925
R^2		0.079	0.345	0.193	0.558	0.558
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
HQ Country	Yes	Yes	Yes	Yes	Yes	Yes
Occupation			Yes			
Employer				Yes		
Occupation x Employer					Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Notes: Standard errors clustered at the country dyad level are in parentheses.

Online Appendix Section F. Moderators

This section discusses the construction of our four moderators: (1) whether a job requires a college degree, (2) whether it requires any occupational certification, (3) whether it requires any work experience, and (4) the preparation level required for the job.

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 a bachelor's degree or higher. In our sample, 15 percent of jobs require a bachelor's degree or higher; 85 percent require a degree lower than bachelor's, including an associate degree. We only consider those jobs explicitly require a bachelor's degree or higher as requiring a college degree and treat the other jobs as not requiring such a degree.

Similarly, we code a job as having work experience requirements if it explicitly requires any work experience, which 47 percent of jobs do. It is important to note that many jobs may implicitly require a college degree or some work experience without explicitly mentioning such requirement in a job posting. For example, a lead engineer position is likely to require a college degree, but the employer may regard such requirement as so obvious that she does not bother to put it in the posting. 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 also 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 driver in the United Kingdom is the occupation with the highest number of certifications, with 4.03 certifications; industrial and production engineer in Greece is the second highest with 3.19 certifications, and electronic engineer in Portugal is the third highest with 2.92 certifications.

Finally, we use the O*NET coding to categorize occupations into one of the five preparation levels. O*NET divides all jobs into five zones, based on the level of education, training, and experience required for the job. 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, and 35 percent in zone 2 and 2 percent in zone 1.

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

[Insert Table Online Appendix F.1 about here]

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

	Local Model		Bilateral Model	
	(1)	(2)	(3)	(4)
Social Trust (Local Country)	0.266***	0.299***		
	(0.0590)	(0.0561)		
Social Trust (Local Country) x Occupational Certificates	-0.194	-0.236		
	(0.115)	(0.147)		
Social Trust (HQ-Local)			0.321***	0.301***
			(0.0672)	(0.0676)
Social Trust (HQ-Local) x Occupational Certificates			-0.131*	-0.140**
			(0.0600)	(0.0541)
Occupational Certificates	0.0368	0.0959	0.388*	0.416*
	(0.0546)	(0.0699)	(0.179)	(0.162)
Observations	7415110	7415110	572195	572195
R^2	0.562	0.562	0.507	0.507
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-Level Controls		Included		Included
Job-Level 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. Local models are clustered at the country level, and bilateral models are clustered at the country dyad level.

Online Appendix Section G. Mediation Analysis

Our theory suggests that social trust influences employers' skill preferences through (a). a long-term commitment, and (b). role flexibility. When social trust is high, employers and employees tend to perceive their relationship as a long-term collaboration, encouraging employers to invest in employee skills. At the same time, employers are more open to granting employees role flexibility, which in turn requires stronger foundational skills. In this sense, social trust is an indirect predictor of employers' preferences for foundational skills, whereas employees' job tenure and role flexibility are direct predictors.

To test this argument directly, we first measure employees' job tenure using public LinkedIn data. The LinkedIn data covers all 28 EU countries in our sample. Our data is at the employee-occupation level, with each employee potentially having multiple positions. We only consider entries with more than 100 observations in each occupation-country cell. To calculate job tenures, we subtract each individual's starting year from their ending year and add one. This process results in a dataset containing 23,015,977 observations with valid occupation and employer information. Within each occupation-country group, we determine job tenure by averaging the tenures of individuals within their current organizations. Second, we measure role flexibility at the firm-year level using our job posting data. One of the ESCO skills is *adapt to change*, which reflects employers' expectations for their employees to respond quickly to the changing environment and adapt to varying job responsibilities. Around 61 percent of jobs listed this skill. We measure the percentage of jobs mentioning such a skill in each firm-year cell as a proxy for role flexibility in the firm. We then use both job tenure and role flexibility measures to run the mediation analysis.

Table Online Appendix G.1 presents the mediating role of job tenure. Following Baron and Kenny (1986), De Jong and Elfring (2010) and Malhotra et al., (2018), we estimated three stages of separate regression equations. Models 1-4 present results without country controls, and models 5-8 present results using the same model specifications with country countries. In the first stage, we regress employers' preference for foundational skills on social trust and the control variables, thus confirming the effect of trust on employers' skill preferences (model 1 and model 5). In the second stage, we regress job tenure at the occupation-country level on social trust, and the results (model 2 and model 6) show that trust has a significant and positive relationship with job tenure. Next, we regress employers' preference for foundational skills on job tenure. Models 3 and model 7 show that job tenure has a positive and significant relationship with employers' skill preferences: jobs with longer tenure tend to require more foundational skills rather than advanced skills. Finally, we regressed employers' preference for foundational skills on social trust, job tenure, and the control variables, and model 4 and model 8 shows that the significant and positive relationships between social trust and employers' preference for foundational skills that we found in model 1 and model 4 are reduced. Complementing the 3-step approach, we followed Preacher and Hayes (2008) and ran a Monte Carlo simulation to determine the significance of the mediated effect. Our results confirm the mediating effect of job tenure on employers' preferences for foundational skills (Monte Carlo 95% confidence interval of (0.02, 0.05)). The results suggest that job tenure partially mediates the relationship between social trust and employers' preferences for foundational skills.

[Insert Table Online Appendix G.1 about here]

Similarly, Table Online Appendix G.2 presents the mediating role of role flexibility. We followed the above steps and find role flexibility partially mediates the relationship between social trust and employers' preferences for foundational skills (Monte Carlo 95% confidence interval of (0.06, 0.16)). Overall, job tenure explains 14-23 percent of the effect of trust on skill preferences, and role flexibility explains 3-8 percent of the effect of trust on skill preferences. Figure Online Appendix G.1 presents the result of our mediation test, decomposing the indirect relationship (via job tenure and role flexibility) and the direct relationship of social trust on employers' preference for foundational skills.

[Insert Table Online Appendix G.2 about here]

[Insert Figure Online Appendix G.1 about here]

In Table Online Appendix G.3, we include both job tenure and role flexibility as mediators. Consistent with our results above, including both mediators in the same model partially explain the effect of trust on skill preference by 17-30 percent.

[Insert Table Online Appendix G.3 about here]

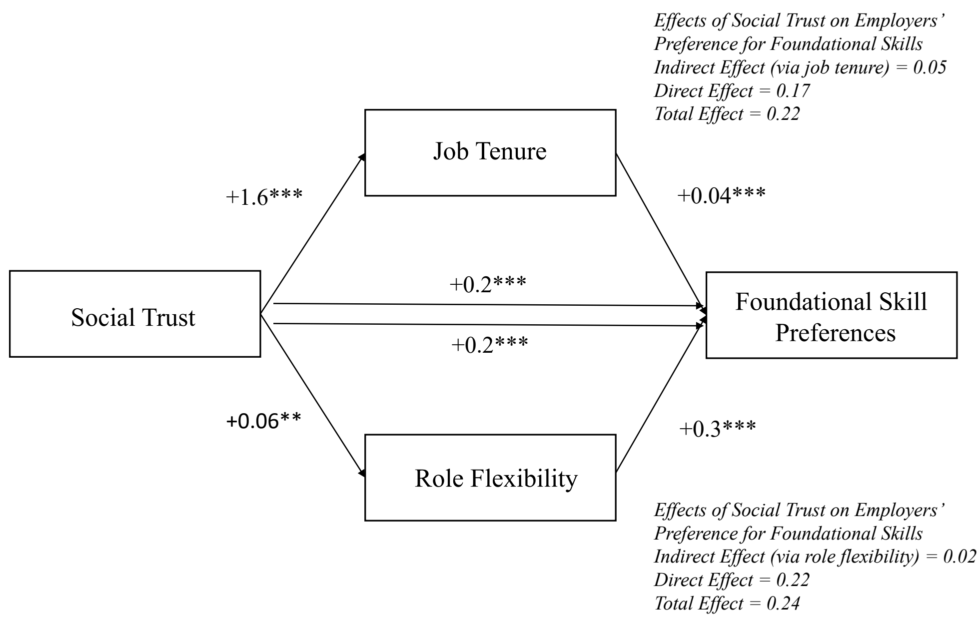


Figure Online Appendix G.1: The Mediating Effect of Job Tenure and Role Flexibility

Table Online Appendix G.1: Linear Estimation Predicting Preference for Foundational Skills: The Mediating Role of Job Tenure

	Without Country Controls				With Country Controls			
	(1) Foundational Skills	(2) Job Tenure	(3) Foundational Skills	(4) Foundational Skills	(5) Foundational Skills	(6) Job Tenure	(7) Foundational Skills	(8) Foundational Skills
Social Trust (Local Country)	0.262***	1.089***		0.226**	0.222***	1.622***		0.171***
	(0.0682)	(0.285)		(0.0752)	(0.0371)	(0.344)		(0.0416)
Job Tenure			0.0442***	0.0328*			0.0387***	0.0315***
			(0.0108)	(0.0138)			(0.00728)	(0.00815)
Job Req. College Degree	0.0102	0.0113	0.0101	0.00986	0.0106	0.00696	0.0108	0.0104
	(0.0205)	(0.00695)	(0.0205)	(0.0204)	(0.0211)	(0.00347)	(0.0212)	(0.0210)
Job Req. Graduate Degree	0.0132	0.00335	0.0132	0.0131	0.0129	0.000776	0.0131	0.0128
	(0.00738)	(0.00461)	(0.00749)	(0.00739)	(0.00766)	(0.00238)	(0.00776)	(0.00764)
Job Req. Short-Cycle Tertiary Degree	0.00511	-0.00130	0.00497	0.00515	0.00518	-0.000482	0.00506	0.00520
	(0.00668)	(0.00167)	(0.00665)	(0.00668)	(0.00660)	(0.000897)	(0.00657)	(0.00660)
Job Req. Non-Tertiary Degree	0.0233*	0.00895	0.0235*	0.0231*	0.0238*	0.00567	0.0242*	0.0236*
	(0.0102)	(0.00618)	(0.0102)	(0.0101)	(0.0106)	(0.00326)	(0.0106)	(0.0105)
Job Req. Work Experience	-0.000276	0.000230	-0.000310	-0.000284	-0.000293	-0.0000533	-0.000281	-0.000292
	(0.00552)	(0.000269)	(0.00551)	(0.00552)	(0.00553)	(0.000221)	(0.00553)	(0.00553)
Num of Skills Listed (log)	-0.0262	-0.0000342	-0.0260	-0.0262	-0.0262	0.000280	-0.0262	-0.0262
	(0.0191)	(0.000601)	(0.0191)	(0.0191)	(0.0191)	(0.000396)	(0.0191)	(0.0191)
GDP per Capita (log) (Local Country)					0.0824*	0.673**	0.0623	0.0612
					(0.0388)	(0.193)	(0.0350)	(0.0373)
Human Capital Index (Local Country)					-0.988**	-5.660**	-0.556	-0.809**
					(0.298)	(2.004)	(0.274)	(0.256)
Rule of Law (Local Country)					-0.00948	-0.293**	0.0212	-0.000252
					(0.0204)	(0.104)	(0.0180)	(0.0201)
Unemployment Rate (Local Country)					-0.573*	-3.184*	-0.152	-0.473
					(0.253)	(1.477)	(0.231)	(0.238)
% of Graduates from Vocational Education (Local Country)					-0.0867	1.260**	-0.113	-0.126
					(0.0729)	(0.357)	(0.0736)	(0.0672)
Collective Bargaining Coverage (Local Country)					0.102*	-0.242	0.0926*	0.110**
					(0.0410)	(0.168)	(0.0394)	(0.0391)
Observations	9285032	9285032	9285032	9285032	9285032	9285032	9285032	9285032
R^2	0.572	0.995	0.572	0.572	0.572	0.996	0.572	0.572
Fixed Effects:								
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Employer	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Notes: The table shows the mediating model for our main analysis. Standard errors clustered at the country level are in parentheses.

Table Online Appendix G.2: Linear Estimation Predicting Preference for Foundational Skills: The Mediating Role of Role Flexibility

	Without Country Controls				With Country Controls			
	(1) Foundational Skills	(2) Role Flexibility	(3) Foundational Skills	(4) Foundational Skills	(5) Foundational Skills	(6) Role Flexibility	(7) Foundational Skills	(8) Foundational Skills
Social Trust (Local Country)	0.292** (0.0800)	0.0363*** (0.00590)		0.282** (0.0798)	0.240*** (0.0453)	0.0630** (0.0178)		0.221*** (0.0466)
Role Flexibility			0.300*** (0.0271)	0.299*** (0.0273)			0.299*** (0.0271)	0.299*** (0.0272)
Job Req. College Degree	0.0184 (0.0188)	-0.00335*** (0.000801)	0.0199 (0.0188)	0.0194 (0.0187)	0.0189 (0.0195)	-0.00342*** (0.000788)	0.0207 (0.0196)	0.0200 (0.0193)
Job Req. Graduate Degree	0.0214** (0.00710)	-0.00433*** (0.00100)	0.0228** (0.00695)	0.0227** (0.00679)	0.0211** (0.00748)	-0.00439*** (0.000992)	0.0227** (0.00736)	0.0224** (0.00716)
Job Req. Short-Cycle Tertiary Degree	0.00636 (0.00967)	-0.00555*** (0.000704)	0.00781 (0.00952)	0.00802 (0.00956)	0.00645 (0.00958)	-0.00553*** (0.000706)	0.00791 (0.00942)	0.00811 (0.00948)
Job Req. Non-Tertiary Degree	0.0275* (0.0106)	-0.00270*** (0.000622)	0.0290* (0.0106)	0.0283* (0.0105)	0.0282* (0.0110)	-0.00279*** (0.000617)	0.0299* (0.0112)	0.0290* (0.0109)
Job Req. Work Experience	-0.00803 (0.00560)	0.00309 (0.00228)	-0.00898 (0.00556)	-0.00895 (0.00556)	-0.00803 (0.00560)	0.00307 (0.00228)	-0.00894 (0.00557)	-0.00895 (0.00557)
Num of Skills Listed (log)	-0.0321 (0.0184)	0.000303 (0.00151)	-0.0320 (0.0182)	-0.0322 (0.0182)	-0.0321 (0.0184)	0.000296 (0.00151)	-0.0322 (0.0182)	-0.0322 (0.0182)
GDP per Capita (log) (Local Country)					0.120** (0.0374)	0.0123* (0.00465)	0.124** (0.0376)	0.116** (0.0371)
Human Capital Index (Local Country)					-1.375*** (0.296)	-0.0837 (0.0523)	-1.081** (0.324)	-1.350*** (0.295)
Rule of Law (Local Country)					-0.0194 (0.0155)	-0.0162** (0.00497)	0.0115 (0.0170)	-0.0146 (0.0149)
Unemployment Rate (Local Country)					-0.822** (0.226)	-0.225*** (0.0565)	-0.386 (0.266)	-0.755** (0.223)
% of Graduates from Vocational Education (Local Country)					-0.162* (0.0665)	0.000783 (0.00964)	-0.135 (0.0826)	-0.162* (0.0669)
Collective Bargaining Coverage (Local Country)					0.121* (0.0522)	0.00675 (0.00625)	0.0936 (0.0545)	0.119* (0.0517)
Observations	13957883	13957883	13957883	13957883	13957883	13957883	13957883	13957883
R^2	0.595	0.911	0.595	0.595	0.595	0.911	0.595	0.595
Fixed Effects:								
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Employer	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: The table shows the mediating model for our main analysis. Standard errors clustered at the country level are in parentheses.

Table Online Appendix G.3: Linear Estimation Predicting Preference for Foundational Skills: The Mediating Role of Job Tenure and Role Flexibility

	Without Country Controls			With Country Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Social Trust (Local Country)	0.262***		0.215**	0.222***		0.154***
	(0.0682)		(0.0748)	(0.0371)		(0.0402)
Job Tenure		0.0432***	0.0323*		0.0381***	0.0316***
		(0.0109)	(0.0138)		(0.00716)	(0.00812)
Role Flexibility		0.310***	0.310***		0.310***	0.310***
		(0.0349)	(0.0350)		(0.0350)	(0.0350)
Job Req. College Degree	0.0102	0.0114	0.0111	0.0106	0.0120	0.0116
	(0.0205)	(0.0203)	(0.0202)	(0.0211)	(0.0210)	(0.0208)
Job Req. Graduate Degree	0.0132	0.0149*	0.0148*	0.0129	0.0147	0.0145
	(0.00738)	(0.00721)	(0.00712)	(0.00766)	(0.00747)	(0.00736)
Job Req. Short-Cycle Tertiary Degree	0.00511	0.00693	0.00709	0.00518	0.00702	0.00714
	(0.00668)	(0.00653)	(0.00656)	(0.00660)	(0.00646)	(0.00649)
Job Req. Non-Tertiary Degree	0.0233*	0.0245*	0.0240*	0.0238*	0.0251*	0.0246*
	(0.0102)	(0.00999)	(0.00993)	(0.0106)	(0.0105)	(0.0103)
Job Req. Work Experience	0.000276	0.00134	0.00131	0.000293	0.00130	0.00131
	(0.00552)	(0.00506)	(0.00507)	(0.00553)	(0.00508)	(0.00509)
Num. of Skills (log)	-0.0262	-0.0265	-0.0267	-0.0262	-0.0267	-0.0267
	(0.0191)	(0.0187)	(0.0188)	(0.0191)	(0.0188)	(0.0188)
GDP per Capita (log) (Local Country)				0.0824*	0.0590	0.0580
				(0.0388)	(0.0343)	(0.0365)
Human Capital Index (Local Country)				-0.988**	-0.561*	-0.788**
				(0.298)	(0.271)	(0.248)
Rule of Law (Local Country)				-0.00948	0.0231	0.00387
				(0.0204)	(0.0175)	(0.0192)
Unemployment Rate (Local Country)				-0.573*	-0.107	-0.395
				(0.253)	(0.222)	(0.233)
% of Graduates from Vocational Education (Local Country)				-0.0867	-0.113	-0.125
				(0.0729)	(0.0723)	(0.0670)
Collective Bargaining Coverage (Local Country)				0.102*	0.0913*	0.107*
				(0.0410)	(0.0387)	(0.0387)
Observations	9285032	9249992	9249992	9285032	9249992	9249992
R^2	0.572	0.567	0.567	0.572	0.567	0.567
Fixed Effects:						
Posting Year	Yes	Yes	Yes	Yes	Yes	Yes
Posting Month	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Employer	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: The table shows the mediating model for our main analysis. Standard errors clustered at the country level are in parentheses.

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