Online Appendix

Does Turnover Inhibit Specialization?

Evidence from a Skill Survey in Peru

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A Sample design and data collection: additional details

Sampling strategy We excluded non-employer firms. To ensure representativeness, we over-sampled small enterprises (less than 3 employees) and explicitly included employers in the public sector — both public administration and state-owned enterprises.
Workers are sampled according to the distribution of working-age individuals. We consider 16-65 as working age and restrict our attention to provinces where the labor force features at least 1% of college graduates. The latter restriction is largely inconsequential for urban markets.

Validation and quality checks Our surveys collect various variables of auxiliary interest, in addition to the core ones mentioned in the text. From managers/employers, we also collect demographic details such as age and gender about both the employee hired for the position of interest (if present) and the hiring manager. We separately conduct a survey of managers to assess bias in skill reporting for employees of diverse backgrounds and enhance the quality of the reported skill data. Finally, workers further report information on their major and university of graduation, their current employment status, usual hours worked, current wage, and past wages for the last 10 jobs. They also are interviewed about their job search methods and satisfaction level on their current job, in addition to several measures of self-reported skill mismatch. We use a combination of these variables to validate and cross-check the quality of our data.

Firms' Questionnaire [Selected questions]
Hiring manager information
1.1 Sex/gender of the interviewee (don't ask, observe)
1.2 Date of birth
1.4 Highest educational level achieved
1.5 What did you major in as an undergraduate? [major list]
1.6 Where did you get your bachelor's degree? [institution list]

Latest vacancy information
2.2 Think about the last position for which you actively recruited. What was the occupation for which you were recruiting for?
2.3 You previously mentioned hiring for a [occupation]. Were you able to find someone to fill this position?

2.4.0 Can you tell me what is the highest educational level achieved by the person you hired to perform [occupation]?

2.4 You mentioned that the name of the occupation is [occupation]. Please name the THREE most important tasks that a person in that position performs or would perform.

2.5 On the same occupation: Could a person with the following levels of education adequately perform the tasks of that occupation?

a. A person without any education

b. A person with a high school education

c. A person with technical formation

d. A person with a bachelor's degree

2.6 How much experience does this position require?

2.7 Keep thinking about the hire you made for [occupation]. What is/was the (approximate) age of the employee when he/she started working?

Demand for skills

3.0 How important are the following skills in performing [occupation]'s tasks? [From 1-least important, to 5-most important] *Note: examples were provided separately by the enumerator, using a table similar to table B.*

3.1 Cognitive skills

3.2 Social skills

3.3 Organizational skills and autonomy

3.4 Writing skills

3.5 Customer service skills

3.6 Project management skills

3.7 People management skills

3.8 Financial skills

3.9 Basic computer skills

3.10 Advanced computer skills

3.11 What do you consider to be suitable bachelor's degrees for the position of [occupation]?

Recruitment and hiring

4.1 Which of the following recruiting methods did your company use to search for candidates to fill a vacancy for [occupation]? (Check all that apply)

a. Universities' job boards

b. Other job boards

c. Newspapers

d. Social media

e. Mass recruitment campaigns

f. Job fairs

g. Recommendations from workers within the company

h. Recommendations from people outside the company

i. Agreements with universities

j. Other

4.2 When the company needs to recruit an employee for a position of [occupation], how long in advance of the start of the contract do you begin searching for that profile?

4.3 In the last 12 months, what percentage of vacancies were filled on time?

4.10 Does the company provide training for new employees?

Perceptions

4.9 I'm going to show you a list of characteristics of potential workers. Please indicate whether you see these characteristics as POSITIVE, NEUTRAL, OR NEGATIVE.

4.9.a The candidate grew up in the same region as one of your employees or yours

4.9.b The candidate graduated from the same university as you or some of your employees

4.9.c The candidate has the same bachelor's degree as some of your employees or you

4.9.e The candidate is of the same sex/gender as you

4.9.f The candidate speaks native/indigenous languages

4.9.g The candidate is not an only child

4.9.h The candidate studied at a private university

4.9.i The candidate studied at a public university

B On the measurement of skills

We create 10 job skill dimensions following the O*NET skills classification and Deming and Kahn (2018), to whom we are indebted in this respect. We survey employers and workers about the importance of each skill category for the job using a scale between 1 (not important at all) and 5 (extremely important). Table B lists the 10 skill dimensions, the examples we provided to the survey participants, and the corresponding O*NET skills. In an effort to guarantee comparability between US and Peruvian skill profiles, we based the examples provided to survey participants on O*NET skills as shown in columns 2 and 3 of Table B.

The first two skills listed in table B are "cognitive" and "social." The description of these dimensions are meant to match the definition of "non-routine analytical" job tasks used in Autor, Levy and Murnane (2003). The third skill, "organization/ self-efficacy," refers to non-cognitive or "soft" skills such as "organized," "detail-oriented," and "time management." The other seven job skill categories are common to a wide range of jobs (Deming and Kahn, 2018). We include categories for basic and advanced computer skills in our survey. The former encompasses common software, such as Microsoft Excel, while the latter includes specialized software.[1]

We measure the importance of each job skill dimension at the occupation level. In Peru, the importance of a given job skill dimension for an occupation is the average importance reported by employers recruiting in such occupations. We use worker-derived data for robustness and find only negligible differences. In the US, the importance of a given job skill dimension for an occupation is given, first, by the simple average importance of the selected O*NET detailed skills contained in the skill dimension (column 3 in Table B), then averaged once again at the occupation level.

[1] "Basic computer skills" doesn't exist in O*NET as a stand-alone skill, therefore, we omitted it from baseline calculations and labeled advanced computer skills as "computer skills", for a finally tally of 9 skill dimensions. As a robustness check, we computed the US importance for this category using O*NET "Tools and Technology" importance scores for each occupation. Specifically, the relative importance of "basic" software in the list of programs required for each occupation. Our results are practically unchanged.

Table B.1: Description of Job Skills

Job Skill Dimension	Questionnaire Examples	O*NET Skills
Cognitive	Problem solving, research, analysis, critical thinking, mathematics, statistics	Reading comprehension, mathematics, science, critical thinking, active learning, learning strategies, complex problem solving, operations analysis, technology design, equipment selection, installation, equipment maintenance, troubleshooting, repairing, quality control analysis, judgment and decision making
Social	Communication, teamwork, collaboration, negotiation, presentation skills	Active listening, speaking, social perceptiveness, coordination, negotiation
Organization/ Self-efficacy	Time management, organized, detail-oriented, multi-tasking, meeting deadlines on time, energetic	Time management
Writing	Writing skills	Writing
Customer service	Sales, patient	Persuasion, service orientation
Project management	Project management	Operation monitoring, operation and control, management of material resources
People management	Monitoring, leadership, management (not project), advisory, personnel	Monitoring, instructing, management of personnel resources
Financial	Budgeting, accounting, finance, costs projection	Management of financial resources
Basic computer skills	Spreadsheets, common software (e.g., Microsoft Excel, PowerPoint).	Common software technology requirement
Advanced computer skills	Programming language or specialized software (e.g., SAP, SPSS, R, Corel, Java, SQL, Python)	Programming systems analysis, systems evaluation, specialized software

Note: Authors' categorization of job skills and correspondence to O*NET skills.

C Summary statistics from the data

Table C.1: Individual characteristics (SSERB-Peru)

	%$^{(i)}$
Female	47.60
Aged 20-25 years	45.26
Aged 26+ years	27.63
Graduated 1 year ago or sooner	30.59
Graduated between 1 and 2 years ago	37.14
Graduated 3 years ago or earlier	5.63
Exactly one job since graduation	44.72
At least one job since graduation	64.92
Self-employed since graduation	2.69
Current occupation: professional$^{(ii)}$	47.85
Current occupation requires college	33.14
Formal job	22.46
Informal job (no benefits, no contract)	25.88
Observations	**11,287**

Notes: Percentage of workers by selected characteristics. $^{(i)}$Percentages may not add up to 100% because of unreported missing values or because categories are not exclusive. $^{(ii)}$Professional occupations may or may not require a college degree. Those that do not require a college degree include private sector managers and public officials, professional positions requiring technical degrees, and administrative bosses/employees. Non-professional occupations include service/retail workers, agriculture workers, construction workers, mechanical workers, and elementary jobs. Source: Authors' calculations based on the SSERB-Peru.

Table C.2: Employers' characteristics (SSERB-Peru)

	Sample	National
Size		
Small	23.5	87.6
Medium	47.9	11.2
Large	28.6	1.1
Sector		
Services & Private Education	39.5	33.9
Wholesale and Retail Trade	17.0	45.0
Construction	7.9	2.7
T&TLC	6.1	7.5
Manufacturing	5.0	7.9
Region		
Lima	65.9	45.5
Coastal (excl. Lima)	12.7	21.9
Mountain	20.1	25.7
Jungle	1.3	6.8
Observations	994	2,303,511

Notes: Distribution of firms across size, sector, and region. Size distribution is as follows: small 0-10 employees; medium 11-99 employees; large 100 or more employees. Source: Authors' calculations based on the SSERB-Peru and the 2017 National Firm Survey (ENE 2017, N=19,204) for the sample column and the national size distribution, respectively. National sector and regional distribution from authors' calculations based on INEI (2019)'s Statistics of the 2017 Peruvian Establishments Directory.

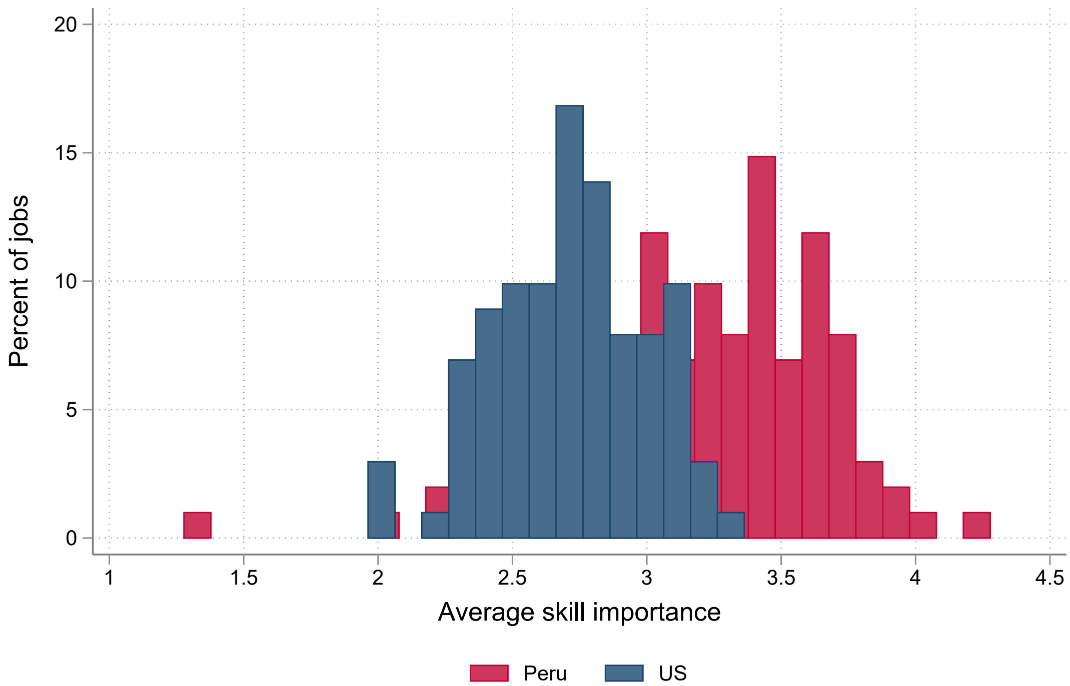
Table C.3: Employers' characteristics (SERB-USA)

	Sample	National[i]
Size		
Small	38.3	89.1
Medium	53.3	10.6
Large	8.3	0.3
Sector		
Natural Resources, Construction & Utilities	5.3	12.5
Wholesale and Retail Trade, Hospitality	15.2	27.4
Professional Services	36.8	56.0
Manufacturing	42.7	4.1
Observations	171	6,075,937

Notes: Distribution of firms across size and sector. Geographical coverage includes the Federal Reserve 5th district, which is Maryland, Virginia, North Carolina, and South Carolina; 49 counties constituting most of West Virginia; and the District of Columbia. Source: Authors' calculations based on the SERB-USA and [i] Census Bureau's 2018 Statistics of US Businesses Annual Datasets. Small firms are identified as 1-50 employees in the SERB USA (Sample) and 1-20 employees in the SUBS (National). Medium firms are identified as 51-499 employees in the SERB USA (Sample) and 21-499 employees in the SUBS (National). Large firms are those with 500+ employees in both surveys.

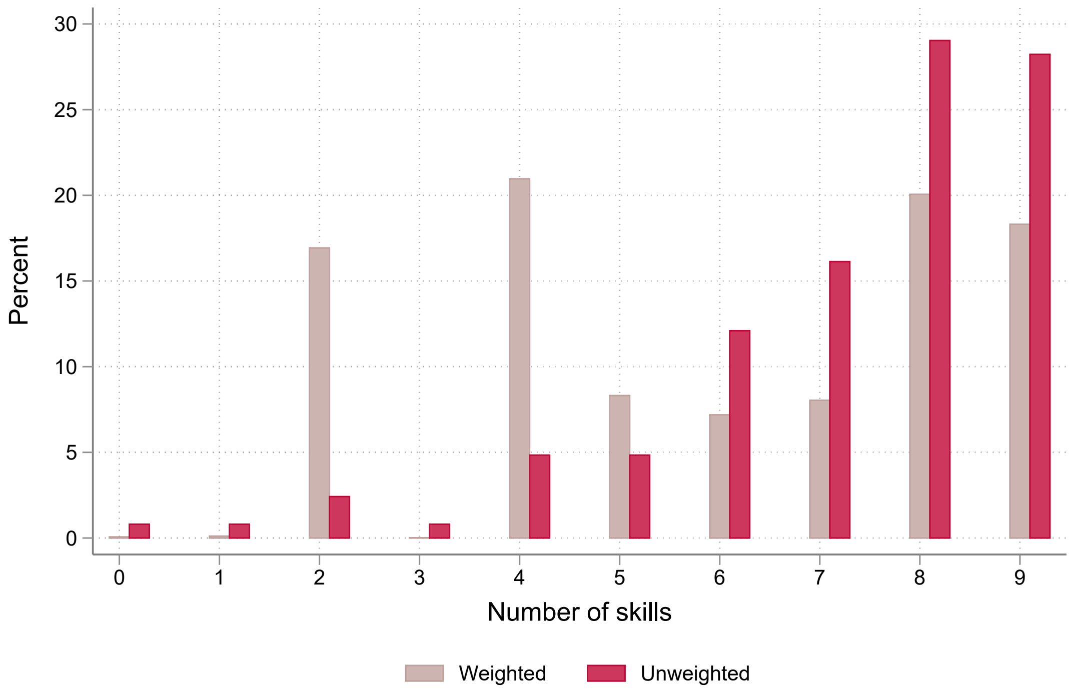
D Additional empirical results

Figure D.1: The distribution of skills importance in Peru is to the right of that in the US.



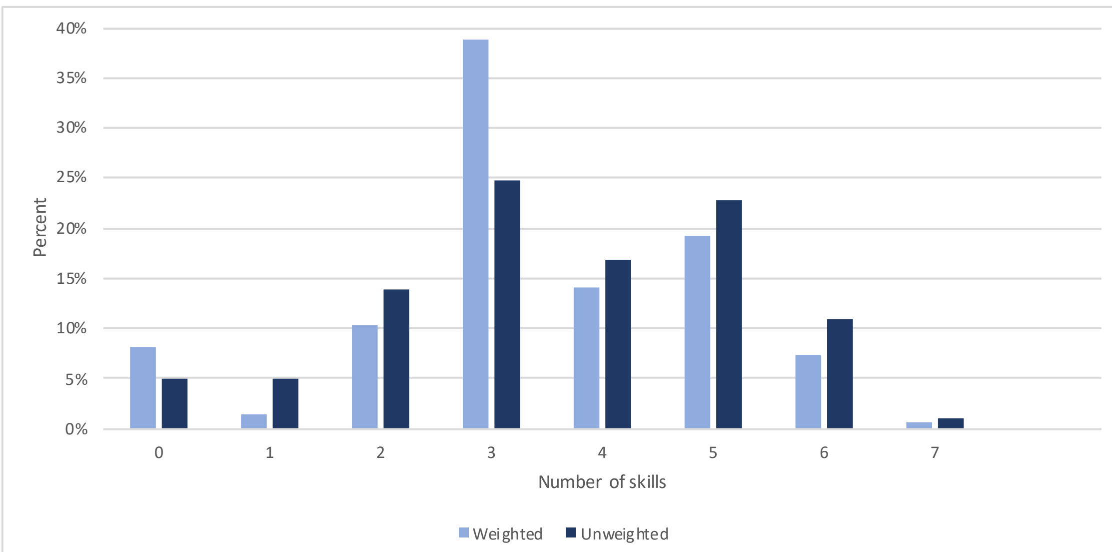
Note: Distribution of average within-occupation skill scores for Peru (red) and the US (blue). Skill assessments are provided by hiring managers, who are asked about the importance of various skill in the last job they actively recruited for. Importance is measured from 1- *not important* to 5-*most important* for 10 different skills. For this plot skill scores are averaged at the occupation level. The plot illustrates the percentage of occupations with different average skill importance scores. For instance, about 8% of jobs in the US have an average skill importance of 3 out of 5, whereas 12% does in Peru. Source: SSERB-Peru and US O*NET 2017.

Figure D.2: When employment-weighted, 18% of Peruvian jobs rates all skills as at least important.



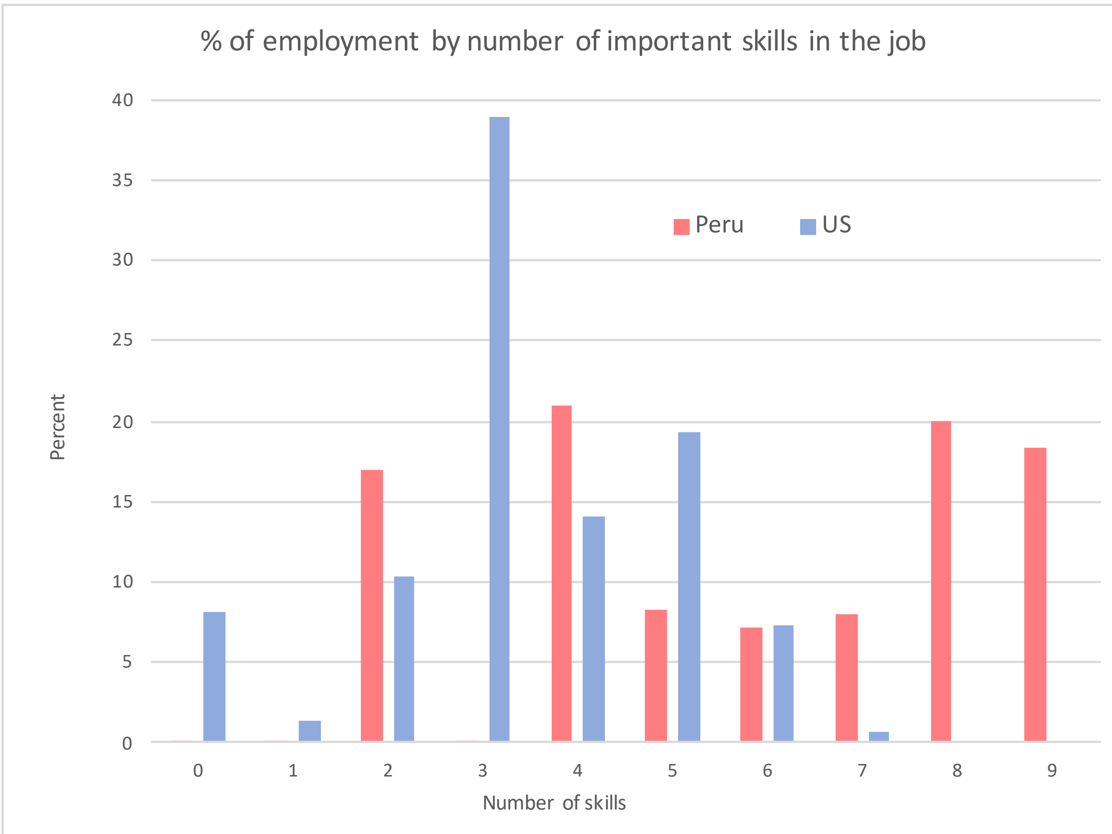
Note: Percentage of employment accounted for by detailed occupations, by number of skill dimensions that are reported to be "important", "very important", or "extremely important" in Peru (red, unweighted; pink, weighted by employment). Skill assessments are provided by hiring managers, who are asked about the importance of various skill in the last job they actively recruited for. Importance is measured from 1- *not important* to 5-*most important* for 10 different skills. "Basic computer skills" doesn't exist in O*NET as a stand-alone skill, therefore, we omitted it from baseline calculations and labeled advanced computer skills as "computer skills", for a finally tally of 9 skill dimensions. For this plot, skill scores are averaged at the occupation-skill level. Employment weights are constructed based on employment in narrow occupation-province cells, as computed from the Peruvian national household survey. The difference between the pink and red bars (weighted and unweighted) lies in the numeraire. For instance, occupations rating 4 skill dimensions as at least important account for less than 5 percent of the occupations, but over 20 percent of employment. Differences are more muted at the top: occupations rating all 9 skill dimensions as at least important account for about 25 percent of the occupations, and 17 percent of employment. Source: SSERB-Peru and ENAHO 2017.

Figure D.3: Few occupations (dark blue) and even fewer workers (light blue) in the US are accounted for by jobs reporting more than 4 skill dimensions as at least "important".



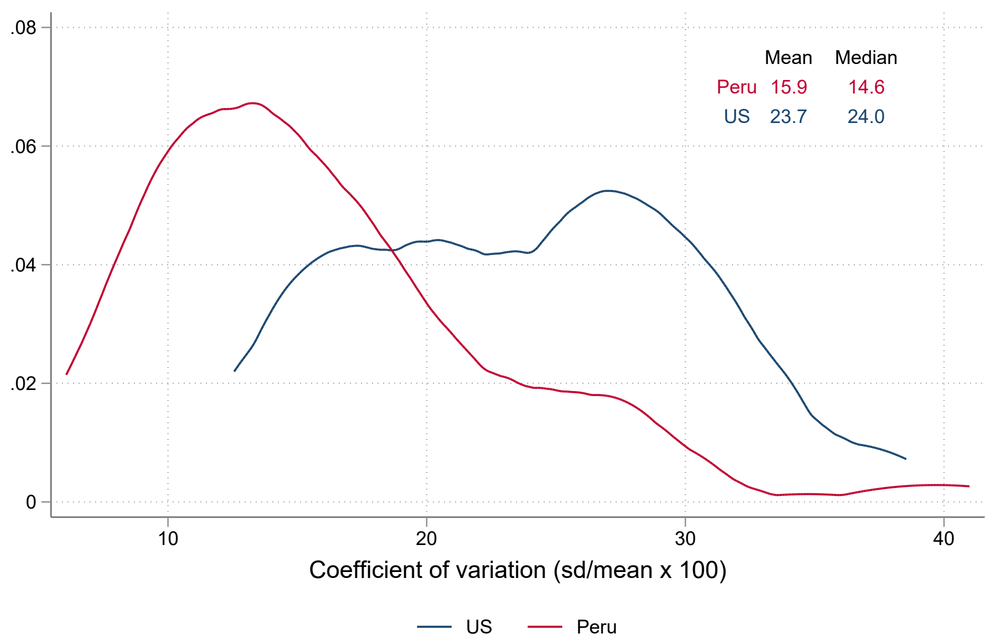
Note: Percentage of employment accounted for by detailed occupations, by number of skill dimensions that are reported to be "important", "very important", or "extremely important" in the US (dark blue, unweighted; light blue, weighted by employment). Skill assessments are derived from O*NET Skills descriptors and employment weights from the American Community Survey, for the year 2017. Skill importance is measured from 1- *not important* to 5-*most important* for 10 different skills. The difference between the light blue and dark blue bars (weighted and unweighted) lies in the numeraire. For instance, occupations rating 3 skill dimensions as at least important account for less than 25 percent of the occupations, but almost 40 percent of employment. Source: O*NET and ACS 2017.

Figure D.4: The share of workers in jobs that indicate 4 or more skill dimensions as at least “important” is larger in Peru than the US.



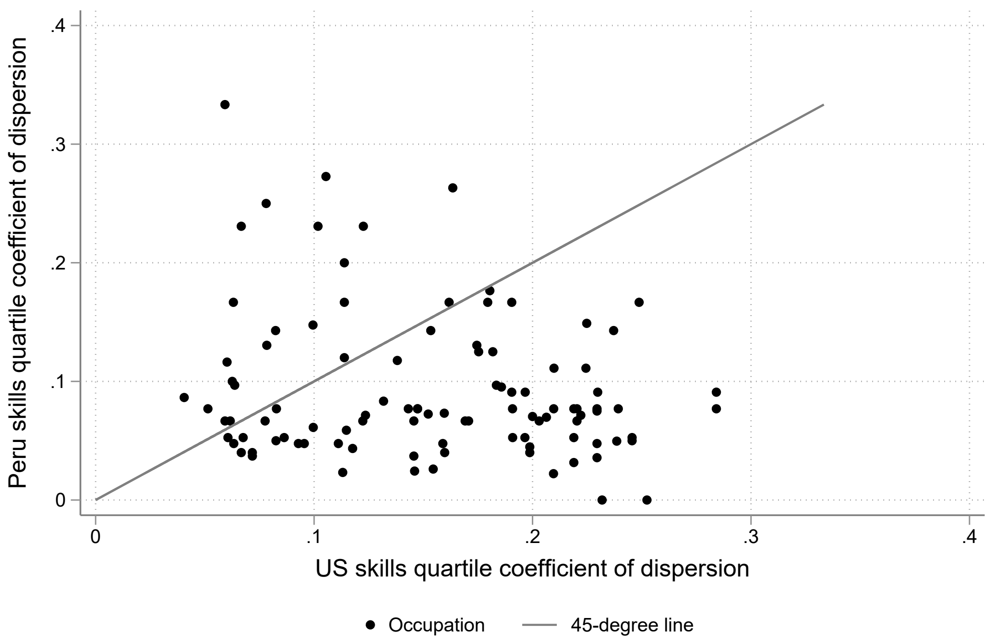
Note: Percentage of employment accounted for by detailed occupations, by number of skill dimensions that are reported to be “important”, “very important”, or “extremely important” in Peru (pink) and the US (light blue). Skill assessments are provided by hiring managers in Peru, and O*NET in the US. In both datasets, importance is measured from 1- *not important* to 5-*most important* for 10 different skills. Employment weights are constructed based on employment in narrow occupation-province cells in the Peruvian national household survey (ENAHO), and occupation cells in the American Community Survey (unlike SSERB-Peru, there is no geographic variation in O*NET so weights compatible with O*NET need not be varying over space). When weighting by employment, more workers are in jobs indicating more skill dimensions as important in Peru than in the US. Source: SSERB-Peru, O*NET, ENAHO, and ACS 2017.

Figure D.5: Peruvian jobs feature a more uniform occupational skill importance distribution than US ones. The within-occupational coefficient of variation is 49% lower than in the US, that is, occupational skill importance scores are 49% less dispersed around their mean than in the US.



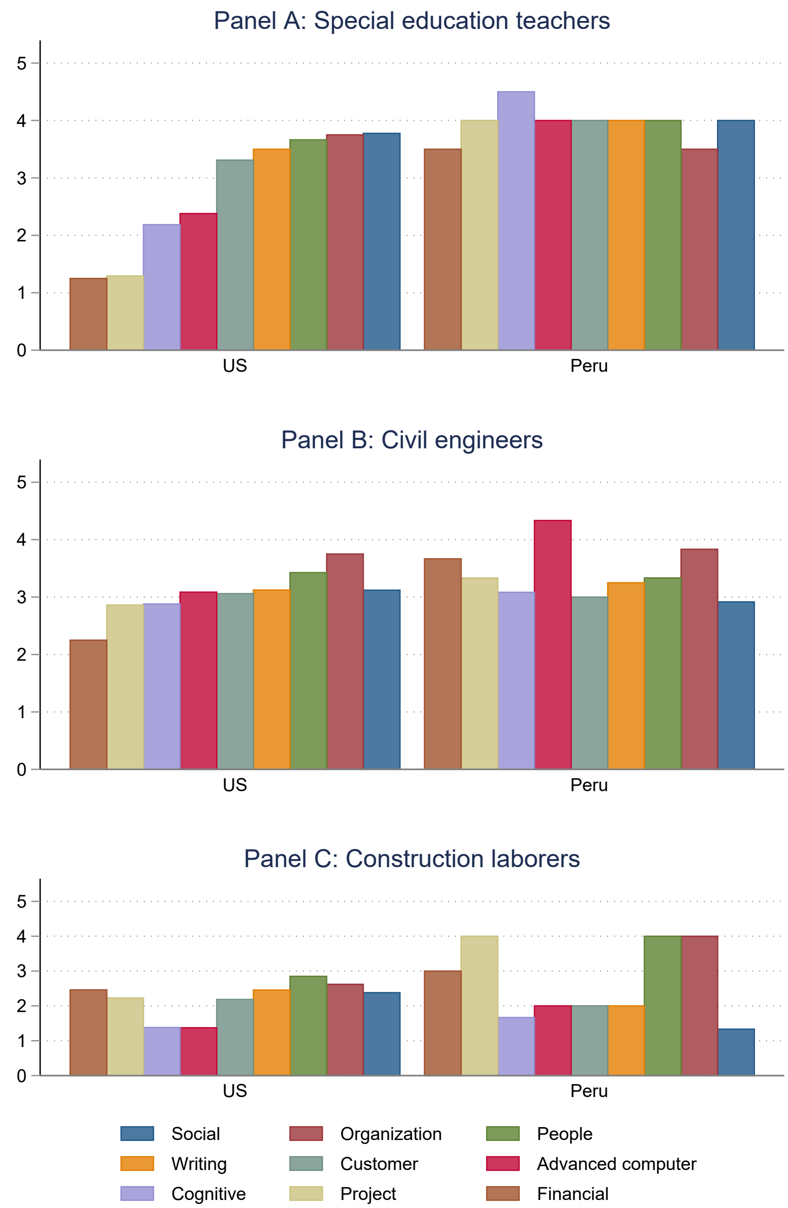
Note: Distribution of the coefficient of variation of occupational skill scores for Peru and the US. Skill scores are provided by hiring managers, who are asked about the importance of various skill in the last job they actively recruited for. Importance is measured from 1- *not important* to 5-*most important* for 10 different skills. For this plot, skill scores are averaged at the skill-occupation level. The CV calculates the dispersion of average within-occupation skill scores around the occupation's mean. It is calculated by dividing the standard deviation by the mean and expressed as a percentage. Source: SSERB-Peru and US O*NET 2017.

Figure D.6: Most jobs in Peru have lower quartile coefficient of dispersion and thus lower specialization than in the US.



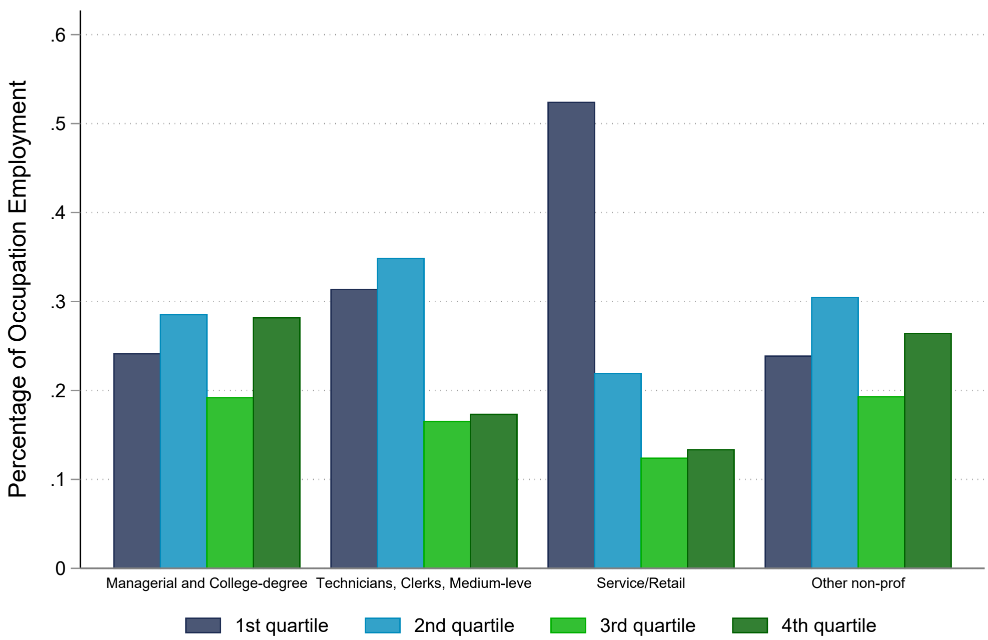
Note: Within-occupation quartile coefficient of dispersion (QCD) for reported skill scores by occupation. Skill scores are provided by hiring managers, who are asked about the importance of various skill in the last job they actively recruited for. Importance is measured from 1- *not important* to 5-*most important* for 10 different skills. For this plot, skill scores are averaged at the skill-occupation level. The QCD is $(Q_3 - Q_1)/(Q_3 + Q_1)$ where Q_1 is the first quartile (the 25th percentile) and Q_3 is the third quartile (the 75th percentile). Peruvian data is on the y-axis and US data on the x-axis. Source: SSERB-Peru and US O*NET 2017.

Figure D.7: Peruvian workers do a little bit of everything, they are “toderos”, regardless of the current occupational title. Hence, the skill importance distribution for Peruvian occupations looks “flat”.



Note: Skill profiles for (A) special education teachers; (B) civil engineers; (C) construction laborers, in the US (left) and Peru (right). Each bar represents the average importance of the skill. “Basic computer skills” doesn’t exist in O*NET as a stand-alone skill, therefore, we omitted it from baseline calculations and labeled advanced computer skills as “computer skills”, for a finally tally of 9 skill dimensions. Source: SSERB-Peru and O*NET 2017.

Figure D.8: In Peru, there are workers in each wage quartile for every major occupational group.



Notes: Each bar represents the percentage of workers of the given occupation whose wage is in the corresponding aggregate wage quartile. Source: SSERB-Peru.

Table D.1: More than 70% of Peruvian jobs report seven or more skills (out of nine) as at least important, regardless of selected firms' characteristics and employee's age.

	Number of skills at least "important"		
	0-3	4-6	7-9
Sector			
Agriculture and Mining	15.79	21.05	63.16
Manufacturing and Construction	9.52	14.29	76.19
Services	5.11	21.17	73.72
Public Sector	1.96	7.84	90.20
Employment size			
Small	4.94	17.28	77.78
Medium	6.78	20.34	72.88
Large	3.45	16.09	80.46
Employee age			
Less than 30	6.08	20.27	73.65
30 or more	6.41	16.67	76.92

Notes: Distribution of detailed occupations across the number of skills reported as "important", "very important", or "extremely important" by firm sector, firm size, and employee's age. Skill scores are provided by hiring managers, who are asked about the importance of various skill in the last job they actively recruited for. Importance is measured from 1- *not important* to 5-*most important* for 10 different skills. Firm size distribution is as follows: small 0-10 employees; medium 11-99 employees; large 100 or more employees. Source: Authors' calculations based on SSERB-Peru.

E Derivation of the job-filling rate

We derive a condition to relate what we observe in the data to f_{et}.
Consider the daily vacancy stock during period t. It is equal to the sum of previous-period unfilled vacancies and the flow of new vacancies. Denote the latter by θ:

$$v_{est} = (1 - f_{et})(1 - \delta_{et})v_{s-1,t} + \theta_t.$$

Notice that the first term encompasses all vacancies that (i) were not filled between t and $t-1$ (with probability $1 - f_{et}$), and (ii) all unfilled vacancies that did not expire between t and $t-1$ (with probability $1 - \delta_{et}$).
Let hires flow for period t, of length τ, be h_{et}. The flow of hires is equal to the stock of vacancies in the previous period by the employer-level job-filling rate, cumulated over the period's length τ:

$$h_{et} = \sum_{s=1}^{\tau} f_{et} v_{es-1,t}. \tag{1}$$

Summing over s and substituting recursively for v_{est-1} gives us

$$v_{et} = [(1 - f_{et})(1 - \delta_{et})]^{\tau} v_{et-1} + \theta_{et} \sum_{s=1}^{\tau} [(1 - f_{et})(1 - \delta_{et})]^{s-1}, \tag{2}$$

where $[(1 - f_{et})(1 - \delta_{et})]^{\tau}$ is what we observe in the Peruvian data for different τ.
Specifically, we have data on vacancy duration by (expected) recruiting period length (Table 1). We postulate a constant daily filling rate and assume that the rate at which unfilled vacancies elapse is zero (this is largely inconsequential and can be relaxed following Davis, Faberman and Haltiwanger, 2013). Then, substituting (2) into (1), we get that the daily filling rates for vacancies with different recruiting period lengths (short f_s^d, medium f_m^d, and long f_ℓ^d) are

$$(1 - f^{3w}) = (1 - f_s^d)^{15} = 0.09 \rightarrow f_s^d = 0.15,$$

$$(1 - f^{9w}) = (1 - f_m^d)^{45} = 0.10 \rightarrow f_m^d = 0.05,$$

$$(1 - f^{32w}) = (1 - f_\ell^d)^{160} = 0.10 \rightarrow f_l^d = 0.01,$$

where we assume there are 5 working days per week and take medians.

F Further discussions on the stylized model

F.1 Value functions and proofs

$V(A,B)$, the value of hiring specialists, and $V(C,C)$, the value of hiring generalists, are given by

$$V(A,B)=\frac{1}{1-\beta(1-\delta)}$$

and

$$V(C,C)=\frac{1}{1-\beta(1-\delta)}\left(\omega^2+\frac{\omega^2\beta\delta}{4}\frac{1+3\beta(1-\delta)}{1-\beta}\right).$$

A proof is offered below.

When a firm hires two specialists, $\mathcal{L}=(A,B)$, it is optimal to allocate entire time of the type A worker to task 1 and the type B worker to 2, which collectively produces one unit of output. When a worker doesn't show up, a firm cannot produce anything. Therefore, the value function of $V(A,B)$ can be written as

$$V(A,B)=1+\beta(1-\delta)V(A,B)$$

because $V(A,\boldsymbol{.})=V(\boldsymbol{.},B)=0$ when one worker doesn't show up. Solving this equation, we get

$$V(A,B)=\frac{1}{1-\beta(1-\delta)}.$$

When a firm hires two generalists, $\mathcal{L}=(C,C)$, it is optimal to allocate one unit of time to task 1 and another unit of time to task 2. The output is ω^2. When a worker doesn't show up, it is optimal for a firm to allocate half a unit of time of the remaining worker to tasks 1 and 2 equally. The output is $(\omega/2)^2$. Therefore, the value function of $V(C,C)$ can be written as

$$V(C,C)=\omega^2+\beta\left(\delta V(C,\boldsymbol{.})+(1-\delta)V(C,C)\right)$$

where

$$V(C,\boldsymbol{.})=(\omega/2)^2+\beta\left(\delta V(C,\boldsymbol{.})+(1-\delta)V(C,C)\right).$$

Solving a system of equations with two unknowns and two equations, we first get

$$V(C,\boldsymbol{.})=\frac{\omega^2}{4}\frac{1+3\beta(1-\delta)}{1-\beta}$$

and we obtain

$$V(C,C)=\frac{1}{1-\beta(1-\delta)}\left(\omega^2+\frac{\omega^2\beta\delta}{4}\frac{1+3\beta(1-\delta)}{1-\beta}\right).$$

F.2 Potential extension of the model

A potential avenue to extend our current model is incorporating a mechanism that generates higher job separation rates in developing countries, instead of taking them as given. Donovan, Lu and Schoellman (2023), for instance, provide two potential explanations. First, marginal employment, such as self-employment, informal work, and low-earnings wage work, drives much of the cross-country differences in labor market flows. Second, developing countries have more initial low-quality matches, but also more rapid exit from them. Our stylized model could be extended to incorporate either channel.

Another possibility is that firms in developing countries face higher idiosyncratic volatility in their productivity.[2] If a firm's labor demand unexpectedly fluctuates over time, it will naturally increase job separation rates and decrease the incentive to train workers into specialists. This hypothesis may not be fully supported in our current context, because Peru has *lower* firm-level productivity volatility compared to other countries of similar income (Asker, Collard-Wexler and De Loecker, 2014). It is, however, a promising avenue for further investigation.

We do not model explictly search and matching of firms and workers. Job finding rates and job separation rates are taken as given, but could be endogenously determined, exploiting off-the-shelf search and matching frameworks. Researchers have shown that, in such contexts, job flows rates are endogenously determined as a function of both individual and market-wide factors. For example, Martellini and Menzio (2020) build a model in which worker's transitions rates remain constant in the face of improvements in the production and search technologies, while Birinci, See and Wee (2020) propose a model where job finding rates remain constant — but job separation rates decrease — when applications increase. If firms invest in identifying good matches under these technological changes, it may encourage more specialization of skills. This question is left for future research.

[2]We appreciate a referee's thoughtful suggestion on this possibility.

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