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Does Turnover Inhibit Specialization? Evidence from a Skill Survey in Peru

Abstract

We design, pilot, and field a new survey of occupational skills in Peru, to investigate human capital differences between poor and rich countries. Though the average skill level is comparable, Peruvian jobs have markedly more uniform skill profiles than jobs in the US. However, matching frictions are no more severe than in the US, and recruiting technology is largely equivalent as well. A model with complementarities in production offers a plausible explanation. Uncertainty about labor availability, more pronounced in poor countries' turbulent labor markets, destabilizes production. This generates an endogenous labor demand preference for unspecialized workers.

JEL-Codes: E240, O110, O470.

Keywords: cross-country productivity differences, human capital, labor reallocation.

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1 Introduction

> In Caracas, they are called *toderos* (do-it-alls), because they indeed do everything; these marginalized workers live on occasional jobs, nibbling work bit by bit: they are servers or servants, stone-cutters or occasional masons, salespeople or street vendors, occasional electricians or plumbers or wall painters or car attendants; simply labor, available for whatever comes. (E. Galeano, *Las venas abiertas de Latinoamerica*, Inter-American Court of Human Rights)

Employer businesses in poorer countries are consistently smaller and less productive than in richer ones, so that employment opportunities hold little promise for broad-based income growth (Krueger, 1983). Firm size disparities also contribute to the aggregate productivity gap between poor and rich countries (Tybout, 2000; Hsieh and Klenow, 2009, 2010, 2014). Recent scholarship has also highlighted how labor markets in poor countries are characterized by higher rates of worker reallocation, without the corresponding productivity improvements. Instead, the brisk pace of reallocation is accompanied by higher unemployment and under-employment risk, and lower returns to human capital (Donovan, Lu and Schoellman, 2023; Bick, Fuchs-Schündeln, Lagakos and Tsujiyama, 2022; Feng, Lagakos and Rauch, forthcoming; Lagakos, Moll, Porzio, Qian and Schoellman, 2018). In poor countries' labor markets, finding and changing jobs is commonplace, but few livelihoods are the better for it.

Our paper addresses the puzzle of a fast-reallocating labor market that nonetheless does not yield productivity enhancements or income growth. We provide new, direct evidence, based on micro-data, on disparities in detailed job skills between poor and rich countries. Despite its significance for the investigation of human capital deficits, data on occupational skills is lacking for poor countries, and our paper directly addresses this gap. We also connect micro-evidence to macro-phenomena and show that lackluster productivity growth, far from being in spite of a fast-paced labor market, can be in fact be exacerbated by it.

We develop the Survey of Skills and Employers Recruiting Behavior (SSERB) to document equilibrium occupational skills across 10 dimensions, closely following the O*NET skill survey that the Bureau of Labor Statistics produces for US jobs. We implement the SSERB with a nationally-representative sample of workers and firms in urban Peru, across over 600 detailed occupations. The data sheds light on the differences between how jobs with analogous occupational titles are performed in Peru and the US. In particular, although differences in the *mean* importance of each skill are somewhat muted, Peruvian jobs have a markedly more uniform *distribution* than jobs in the same occupation in the US. Augmenting our data collection with a survey module on vacancy filling rates and recruiting efforts by employers, we further show that these flatter occupational skill profiles are unlikely to be the product of an especially obsolete or ineffective hiring technology in Peru. We find no evidence for time-to-fill frictions in excess of the US level, nor of additional inefficiencies in the recruiting process in Peru.

We focus first on the detailed measuring of skills as they are used in a variety of occupations. Data collection in Peru took place between November 2017 and March 2018. Surveying is articulated in two stages: first, we randomly sample establishments from the 2017 Peruvian Census of Enterprises, stratified by province, industry, and plant size. Second, we draw a random sample from the Census of Population, selecting individual workers who are between 0 and 6 years from college graduation.[1] We are able to match a third of the workers to their employers in the firms' sample. We survey workers and all hiring managers about the importance of various skills for either the performance of their current job or a job they are recruiting for, as the case may be.

Peruvian workers are "toderos"; their jobs utilize and value a larger set of skills than comparable US jobs. The average reported importance of different skills is higher in Peru, and more jobs report *all* skills as either "important", "very important", or "extremely important" (25% in Peru, and 0% in the US). Overall, occupational skill importance profiles are flatter in Peru than in the US.

Why the more uniform occupational skill profiles in Peru? We investigate first the possibility of ineffective and obsolete hiring technology (cfr. Bloom, Sadun and Van Reenen, 2012 who document significant deficits in management practices). We complement our skill survey with a newly-developed module on the matching and hiring process, including how employers advertise for open jobs, recruit and screen potential candidates, craft contracts and carry out bargaining, and finally train new employees. Because data on these issues is unavailable for the US as well, we launched a parallel survey in the US, SERB - USA. Data collection in the US was carried out between the beginning of February 2020 and March 2021, surveying hiring managers in the Southeastern U.S.. The goal is to complement JOLTS and O*NET data on job openings and skills, respectively, and provide insights into recruiting technology

[1]Informality is common in Peru and many informal jobs (and some low-skill, low-wage jobs) do not have a clear occupational affiliation or job title, let alone an appropriate comparison occupation in the US. We want to limit the bias introduced by this in our analysis and, to this end, we restrict our attention to jobs held by college-educated workers.

and methods for US firms.

Are Peruvian firms especially slow in filling their vacant positions? Do they use obsolete and ineffective methods to surface and screen job candidates? We do not find evidence of either channel. Open jobs fill quickly in Peru, with an average vacancy duration of 9.1 days, and only 10% (1%) of vacancies remain unfilled after two weeks (4 months). The high job-filling rate is due to a combination of short job advertising duration and high filling rates. Well over two-thirds of Peruvian firms post their vacancies within 4 weeks of the desired start date, and the vast majority of these vacancies are filled within this time frame. Taken with evidence from previous scholarship, our data confirms that the Peruvian labor market is fluid. However, unlike evidence from richer countries suggests, labor market fluidity does *not* necessarily breed prosperity.[2]

Do Peruvian firms draw on a different set of hiring channels than US firms do? We find that most Peruvian employers use more than one recruiting method at a time, often combining more formal avenues like posting ads on a job board with less standardized channels like recommendations from friends and family, or employee referrals. Exploiting family, friends, or co-workers' connections to surface candidates for open jobs, is by far the most popular recruiting channel, alone or alongside other instruments. In the US, results are remarkably similar, with employers relying as much on informal channels and recommendations as they do on job posting. Ultimately, we find very little appreciable difference in recruiting methods. The data furnishes little detectable disparity in the recruiting technology between Peru and the US, either in terms of its speed and its efficiency.

Could a turbulent labor market explain the lack of occupational specialization we document? When there is complementarity in production tasks, high worker reallocation rates mean production losses. Employers are seldom sure what available labor they might find on the factory floor on any specific date, as idiosyncratic shocks buffet workers and their access to transportation, child or elderly care, or their willingness or ability to work for pay. Thus, employers value workers who can perform many tasks to minimize disruptions to production. In turn, employers' preference for "toderos" leads workers to keep a broad skill profile. Lower specialization may further perpetuate frequent separations and fast job-filling, consistent with little incentive to invest in long-term employment relationships and lower returns to experience (as documented by Lagakos, Moll, Porzio, Qian and Schoellman, 2018).

[2]Our result on short vacancy duration and high job-filling rates can be interpreted as the mirror image to higher worker flows, as documented by Donovan, Lu and Schoellman (2023) who reach a similar conclusion regarding the relationship between labor market dynamism and growth.

To illustrate this mechanism, we propose a stylized model in the O-ring tradition. The performance of jobs combines two tasks, and workers may either specialize in one of them or not (workers, therefore, are either specialists or generalists). For each given task, workers who specialize in it are able to produce more output than those who do not. However, if a firm hires two specialists and one of these fails to come to work, the firm produces nothing. This reflects the intuition that some tasks are fundamental for production to happen. Our stylized model delivers that hiring generalists ("toderos") becomes more profitable when the separation rate is high. If exogenous separations occur frequently, firms must often reallocate workers across tasks to maintain output. Turnover and worker absences change the input mix, as employers strive to minimize disruptions to production.

Poor countries' labor markets feature both a high job-separation rate and a high job-filling rate, and Peru is no exception. Our model shows that such a brisk pace of job reallocation has the potential to significantly inhibit occupational skill specialization, potentially contributing to human capital and productivity deficits. We conclude that policy makers in poor countries may see good returns from labor market interventions that do not only seek to enhance job mobility rates, but also explicitly support human capital accumulation and specialization.

Contribution to the literature This paper is most related to the macro literature seeking to document and understand cross-country patterns of labor market conditions and outcomes. Lagakos, Moll, Porzio, Qian and Schoellman (2018) documents that returns to experience are much lower in poor countries than in rich ones. A recent comprehensive effort by Donovan, Lu and Schoellman (2023) uses surveys from 45 countries to show that some of those differences are due to worker flows being two to three times higher in the poorest countries as compared to the richest. Our paper complements the picture these authors paint, and confirms the view of poor countries' labor markets as high-paced but low-rewarded.

Our paper is also closely related to the literature on the importance of labor market frictions in developing countries. The efficient functioning of labor markets crucially depends on the information available to both employers and job seekers, and on the search costs they incur to find each other. A large body of theoretical and empirical work has emphasized the role of information frictions on skills as a potential source of inefficiency (e.g. Pallais (2014) and Farber and Gibbons (1996), among others). Several randomized experiments have also tested various interventions designed to reduce information and search frictions (Abebe, Caria, Fafchamps, Falco, Franklin and Quinn, 2020; Bassi and Nansamba, 2022).[3] We complement current scholarship by providing survey evidence to inform the design of such experiments, as well as the policies they evaluate. We also offer a direction for further investigation of *why* jobs utilize a less specialized set of skills in poorer countries. Our work highlights labor market turbulence and its effects on human capital accumulation, complementing cross-country differences in firm-provided training documented by Ma, Nakab and Vidart (forthcoming), and the lack of specialized time allocation between workers and entrepreneurs investigated by Bassi, Lee, Peter, Porzio, Sen and Tugume (2023) within Ugandan firms.

2 Data

2.1 Peru — Skills and Employers' Recruiting Data

The Survey of Skills and Employers' Recruiting Behavior (SSERB) Peru is our main source of data on occupational skills, and on recruiting inputs, efforts, and hiring yield by employers in Peru.

Sample design Our data is articulated across two surveys representative of workers and firms in urban labor markets. The first survey is addressed to a sample of 1,000 firms, randomly drawn from the Census of Enterprises.[4] The second questionnaire collects information from a cohort of individuals, sampled from the Census of Population, who have obtained their college degree within 6 years of the survey date, and who may or may not be currently employed. About a third of jobs in the employers survey can be reliably traced back to a worker in the individuals sample.

The final datasets are stratified random samples of 5,000 workers and 1,000 employers/jobs. Our final sample includes the provinces of Ancash, Arequipa, Cajamarca, Callao, Cusco, Huanuco, Ica, Junin, La Libertad, Lambayeque, Lima, Piura and Puno — covering over 75% of Peruvian labor force.[5]

We do not regard our focus on college-educated workers as a drawback. We abstract from measuring literacy and numeracy deficits, which are likely to be more important when com-

[3] McKenzie (2017) provides a summary of 9 recent randomized experiments that have tested various interventions on search and matching assistance.

[4] 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.

[5] More details on our survey design are in the online appendix, section B.

paring less-skilled jobs. Instead, we focus on skills utilized in college jobs, which, if anything, will lead to underestimate cross-country differences in human capital. Furthermore, we think the college focus helps ensuring a fair comparison. Many informal, low-skill, low-wage jobs do not have a clear occupational affiliation or job title in Peru, let alone an appropriate comparison occupation in the US. Finally, similar to many other low- and middle-income countries, Peru has seen a sustained increase in college workers over the last 20 years but no comparable growth in yout employment rates.[6] Then, measuring skill deficits for college-educated workers and their jobs is particularly relevant in the Peruvian context.

Measurement The core of our data is the information on skill composition of jobs in Peru, which is present in both the workers sample and the matched employer-employee data. We measure the importance of ten skill dimensions for the performance over 600 occupations. The occupational classification is roughly equivalent to the US SOC 4-digit level, with examples of job titles at this level being Retail Salespersons (*Vendedores*) and Accountants (*Contadores*). We survey both workers and employers about the importance of the following skill categories: cognitive, social, organization, writing, customer service, project management, people management, financial skills, and basic and advanced computer skills. We provide survey participants with examples of each skill category, based on O*NET and Deming and Kahn (2018) (see Table 1 in their paper, and the detailed material provided in online appendix A). For instance, cognitive skills involve problem-solving, research, or critical thinking, math, and statistics. Social skills pertain to collaboration and negotiation. Organization skills are related to time management. Skill importance is measured at the occupation level using a scale between 1 (not important at all) and 5 (extremely important).

To the best of our knowledge, this is the first representative source of data on detailed occupational skills that covers a wide cross-section of occupations in a large developing economy. Our data is also a unique source combining information on occupational skills with establishment-level recruiting and hiring behavior. Indeed, we elicit from participants information on many aspects of the hiring process between workers and jobs. The employers' survey contains information on the most recent position the firm recruited for, including the position's job title, required skills, education and experience levels, methods used to recruit, vacancy duration and yield, obstacles to hiring or contracting, and on-the-job training. In

[6] College enrollment of adults aged 17-24 rose from just below 23% in 2000 to about 35% in 2017. However, there has been no corresponding improvement in the percentage of formal workers or employment prospects for Peruvian youth. While formal employment is stable at 40%, the unemployment rate among young Peruvians (about 10% in 2017) is almost three times higher than that for adults, according to the ILO.

addition, we collect data on employers' size, sector, and main products/services sold.[7]

Descriptive statistics The distribution of the firms in our sample is skewed towards larger enterprises because of the focus on urban areas and formal, higher-skill jobs. As discussed before, this is by design — though we still wish to acknowledge the differences for future researchers. At the national level, three out of every four firms are small, but this share is about one in four in our sample.[8] Our survey under-counts wholesale and retail trade establishments, and construction businesses, and over-represents the capital, Lima.

Individuals in our worker sample are relatively young, as they have typically completed college only a few years before the interview date. Despite their young age, about 2 in 3 have been employed in at least one job since graduation. Despite being college educated, 2 out of 3 workers in our graduates' sample are employed in an occupation that does not require a college degree. In addition, over 1 in 4 college workers are working informally.[9]

2.2 USA

2.2.1 O*NET

O*NET describes 461 4-digit broad occupations in the United States, spanning the years 2000-2022. Its core information is the mix of knowledge, skills, and abilities that occupations require. To conduct our analysis, we match Peruvian job titles to US job titles and corresponding 4-digit SOC codes, and, when needed, enhance the matching process to use not only the main reported job titles, but also alternative job titles and the top 3 tasks reported in both the US and the Peruvian data. We use the Skills descriptor in O*NET and model our Peruvian survey on it. In the O*NET questionnaire, skills are defined as "the ability to perform a task well, usually developed over time through training or experience, that can be

[7]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.

[8]We compare our data with the national distribution of firms as computed by the Peruvian National Institute of Statistics and Information (INEI, for its initials in Spanish) in their 2016 Business Structure report. Details are available in the online appendix, Table C.2.

[9]We have information on contractual benefits and informality for a little less than half of our sample. We define informality as (i) not having a contract, or (ii) having a contract but no access to employer-sponsored benefits such as health insurance, pension savings, and unemployment insurance. Table C.1 in the online appendix provides further details.

used to do work in many jobs or in learning." Workers are asked to indicate "the importance [of each skill] to perform the [worker's] current job" on a scale from 1 to 5. We do exactly the same in our SSERB survey in Peru.

2.2.2 SERB

The Federal Reserve Bank of Richmond's Survey of Employer Recruiting Behavior (SERB) is a quarterly survey series that aims to provide timely insight into current labor market dynamics. The Federal Reserve Bank of Richmond ran three survey waves between 2020 and 2021, sampling 308 distinct employers across various firm size categories and industries. Although the sample focuses on the Southeastern US, we find remarkable parallels to aggregate labor market conditions and a similar industry and firm-size composition to the aggregate economy.[10]

The February 2020 wave focused on what employers do to source candidates for their open jobs and asked respondents about recruiting efforts for the position their firm most recently recruited for in the prior *twelve* months. The subsequent wave covered the same topics as the February 2020 wave, but asked employers about the most recent position recruited for over the previous *three* months. The third and final survey wave asked about recruiting efforts for the typical open position in the last *twelve* months and measured changes in recruiting methods and efforts since February 2020. We use data from all three waves, in combination with JOLTS and DHI data on vacancy flows, yields, and duration, to compare hiring technologies between Peru and the US.

3 Skill flattening in Peru

We retrieve skill profiles for occupations in the US using O*NET data for 2017, and compare importance ratings for each skill dimension across equivalent 4-digit occupations in the SSERB-Peru. Because the SSERB Skills questionnaire was modeled on O*NET, this comparison is appropriate.

We do not find stark differences in the average importance of various skill dimensions in Peru vis-a-vis the US. The mean skill importance scores is 3.3 in Peru and 2.7 in the US, a

[10]See `https://www.richmondfed.org/publications/research/economic_brief/2021/eb_21-28` for details. Note that SERB-USA under-samples smaller firms with less than 50 employees (over 75% in BDS data, but less than 40% in our surveys) and over-samples manufacturing firms (about double the national average at 30% of the sample). More details in the online appendix, table C.3.

small disparity.[11] Instead, we find that, on average, occupational skill profiles are substantially flatter in Peru, with different professional figures doing "a little bit of everything". We formally measure this in a few different ways.

First, we note that all ten skill dimensions are reported as "important", "very important" or "extremely important" for 25% of the jobs in Peru (18%, if employment-weighted). This percentage is zero in the US (Figure 1). Furthermore, we find that the average skill importance rating is 49% more predictive of any given skill importance score in Peru than it would be in US. In other words, the coefficient of variation (CV) within detailed occupations is 15.93 in Peru, versus 23.71 in the US. The CV is simply the ratio of the mean to the standard deviation and its distribution in the two countries implies that Peruvian jobs feature less dispersion around the mean and have flatter, more uniform skill profiles. When we plot the occupational-level coefficient of variation for Peruvian and US jobs against each other (Figure 2), most of the jobs display lower specialization in Peru (i.e., lower coefficient of variation).[12]

Notable examples of such uniform skill profiles are Special Education Teachers, who rate management of financial resources as "very important". While this seemed surprising at first, focus interviews in Peruvian schools and NGOs revealed that such rating is due to the frequent and extensive fundraising and budgeting teachers routinely do. Conversely, construction laborers are more specialized in Peru than in the US. Yet, this is again an expression of the toderos phenomenon. Peruvian construction jobs place higher emphasis on skills related to management of construction projects, or management of financial and human resources — something instead reported as less important in the US data. This is because construction workers in Peru are also a bit managers and a bit accountants.[13] All in all, our evidence supports the "toderos" hypothesis. The average Peruvian job has a similar assessment of the *level* of each skill's importance, but a much more dispersed *distribution* of both skills and tasks than a comparable job in the US.

[11]The online appendix reports the full distribution for completeness, in figure D.1.

[12]For a thorough comparison, we report in figure D.2 the employment-weighted skill importance distribution, and in figure D.3 the full distribution of CV.

[13]The complete skill importance profile of these occupations is in figure D.4. We also report the skill profile for civil engineers, who have the exact same average level of specialization in Peru and the US, emphasizing how technical education and professional tasks tend to act as equalizers across countries. Finally, as a robustness check for occupational skill flattening, we use wage data from the Peruvian household survey ENAHO and verify that the occupational wage distribution is also flat. It is. There is a significant portion of workers in each wage quartile for any given occupational category, as reported in figure D.5.

4 Hiring technology in Peru

4.1 Are firms in Peru slow to hire?

The recruitment process is frictional. A long-standing hypothesis is that such frictions may be particularly severe in poor countries, thus preventing jobs from being filled with timeliness, and firms from growing in size. Is that so? We exploit our data and compute the job-filling rate to investigate this question.

Let e denote the establishment, t time, and f_{et} the job-filling rate for employer e in period t (or the share of filled jobs at employer e during time t). We do not directly observe f_{et} in the data. However, we do observe the share of vacant jobs at e, which are filled at various deadlines since their first advertising. We refer to this time as the (expected) "recruiting period length", which is derived from the time between the day the employer starts recruiting activities and the day the employer expects the job to be filled. We now 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.

Using the proportion of jobs in different recruiting period categories, we find that the aggregate daily filling rate and vacancy duration in Peru are:

$$\tilde{f}^{d,P} = 0.110 \rightarrow 9.06 \text{ days}.$$

A vacancy duration of a little over 9 days is relatively short. Therefore, there seems to be little evidence of especially severe time-to-fill frictions that result in lengthy recruiting or a high share of unfilled vacancies for Peruvian employers.

Comparison to the US We now compare these numbers, which to our knowledge are the first such estimates of their kind outside a rich country, to estimates for the US and find that vacant US jobs are filled at a slower pace than jobs in Peru. For the US, we rely on Davis, Faberman and Haltiwanger (2013)'s calculations. DHI indicators in 2017 report an average of 3.5% daily filling rate[14]; therefore, we get an average vacancy duration of approximately a month, about three times what we documented for Peru:

$$f^{d,US} = 0.035 \rightarrow 28.5 \text{ days}.$$

We conclude that the relatively fast job-filling rate in Peru is consistent with the picture of a fast-paced labor market, as it is also observed from the worker side and documented by Donovan, Lu and Schoellman (2023) using hire and separation flows.

[14] Davis, Faberman and Haltiwanger (2013) report 0.050 as an average for the period 2001-2006 from JOLTS microdata, though the notion of vacancy is more restrictive in JOLTS than in DHI and our own surveys.

4.2 Are firms in Peru inefficient in hiring?

A source of skill deficits and mismatches may be deeply embedded in differences in the recruiting process; that is, the employer's actions between the moment when the need for a new hire arises (the job becomes vacant) and the moment a new hire walks in through the doors (the job is filled). Here, we focus our attention on recruiting methods: how Peruvian firms advertise their jobs and attract suitable candidates, and whether the methods they employ differ from their US counterparts.

Firms in Peru use various recruiting methods. Around 60% of the firms in our sample use more than one method to recruit employees. The most popular recruiting methods rely on networks: referrals from current employees or other professional contacts, recommendations from friends and family, and direct partnerships with educational institutions (Table 2). These hiring methods, alone or in conjunction with other more formal venues, are used by over half of the firms. Jobs requiring less than a college degree and jobs at smaller firms are more likely to recruit candidates only via informal channels. Job posting methods are also popular, with about 50% of employers explicitly advertising their open jobs on a public or semi-public job board. Methods reminiscent of random search, like job fairs or mass recruitment campaigns, are instead used by less than 10% of employers.

Comparison to the US Table 2 also illustrates the comparison between employer recruiting in Peru and the US. The picture it paints is of substantial similarity. Recommendations from friends and family and employee referrals are by far the preferred methods to surface candidates for open jobs. Posting ads on a job board comes as a close second. In the US, 60% and 50% of firms use these two recruiting channels, respectively.[15] Overall, one would be hard-pressed to find evidence of substantial disparities between the two countries in *how* firms recruit new employees.

5 A stylized model with production complementarity and separation shocks

We find no evidence of excess matching frictions or obsolete and inefficient hiring technology in Peru vis-a-vis the US. What, then, can explain uniform occupational skill profiles in Peru? In this section, we show that firms facing complementarity across workers in a turbulent labor

[15] One difference pertains to recruiting with the help of labor market intermediaries such as staffing agencies: 1 in 5 firms takes advantage of this channel in the US, while virtually none do so in Peru.

market would prefer hiring generalists to hiring specialists — an endogenous labor demand response that can account for uniform occupational skill profiles in poor countries.

Poor countries' labor markets feature a high job-separation rate. Peru is not an exception. Donovan, Lu and Schoellman (2023) show that Peru has higher employment exit rates to unemployment, employment exit rates to inactivity, and job/occupation switching rates when compared to the US.[16] Our model reflects this fact in a stylized way and suggests that a lower level of occupational skill specialization, such as that which we documented in Peru, can very well be the results of the brisk pace of job reallocation.

We assume that production consists of many tasks, all of which must be successfully completed for the product to have full value, following the O-ring theory formalized by Kremer (1993). Without loss of generality, we assume that a firm allocates heterogeneous workers' time across two tasks, with the goal to maximize production:

$$y = q_1 * q_2,$$

where q_1 and q_2 are quantities produced given workers' time input in task 1 and 2, respectively.

Workers are endowed with a unit of time that can be allocated to execute different tasks. For simplification, suppose that three types of workers are available in the labor market with the same wage. Type A and B workers are specialists. Type A worker produces one unit of product when she spends a unit of her time to task 1. On the other hand, her time in task 2 produces nothing. Type B worker produces one unit of the product if she spends a unit of her time to task 2. Conversely, her time in task 1 produces nothing. Once a firm hires a specialist, it is optimal to allocate the entirety of their time to their specialties. There is also another type of worker, type C workers. These are generalists, producing $\omega \in (0,1)$ regardless of task assignment.

To prove a role for labor market turbulence, we further assume that a firm hires two workers in period 1 and faces a risk of worker separation with probability δ every next period, for infinite periods. We then compare two cases for the firm's hiring decision: $\mathcal{L} = (A, B)$ or

[16] Figure 1 in Donovan, Lu and Schoellman (2023).

$\mathcal{L} = (C, C)$.[17] The value function is given by

$$V(\mathcal{L}) = \max_{\mathcal{L}} y(\mathcal{L}) + \beta[\delta V(\mathcal{L}_{-1}) + (1-\delta)V(\mathcal{L})],$$

where $\mathcal{L}_{-1}$ is our notation for the state in which one worker does not come to work in a period. The identity of the worker who fails to come to work is random. Firms need time to hire and cannot replace the worker immediately. Furthermore, we do not allow for endogenous separations.

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

$$V(A, B) = \frac{1}{1 - \beta(1-\delta)} \tag{3}$$

and

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

A proof is offered in online appendix E.

The values in equations 3 and 4 are a function of a discount rate β, a separation rate δ, and relative productivity of a generalist, ω. To illustrate the mechanics of the model, we study a numerical example with $\beta = 0.96$ and $\omega = 0.5$ (i.e., a generalist's productivity is half of a specialist's productivity in the specialist's preferred task). We then compare $V(A, B)$ and $V(C, C)$ under different separation rates.

Figure 3 depicts this comparison and shows the values of hiring specialists, $V(A, B)$, and of hiring specialists, $V(C, C)$, for various separation rates. When the separation rate is zero, hiring specialists gives a higher value, because specialists are twice as productive as generalists. With no risk of separation, there is no reason to hire a generalist. Excess value from hiring a generalist comes when we have a non-zero, positive separation rate. When the separation rate increases, both $V(A, B)$ and $V(C, C)$ decrease, but $V(A, B)$ decreases at a faster rate. This is because a firm hiring specialists produces nothing when a specialist worker does not come to work. The cost of random separation can be reduced by hiring generalists instead.

This simple numerical example under our stylized model describes a stark economy in order to make a point. Unexpected worker absences disrupt production and cannot be insured

[17] We can consider other cases, such as hiring one specialist and one generalist. The main point of our stylized model is that hiring one generalist (instead of *two* specialists) becomes more profitable when the separation probability δ increases, so considering other cases would not change the main message.

against ex ante. Therefore, they trigger changes to the equilibrium input mix, as employers strive to minimize output losses.

6 Conclusions

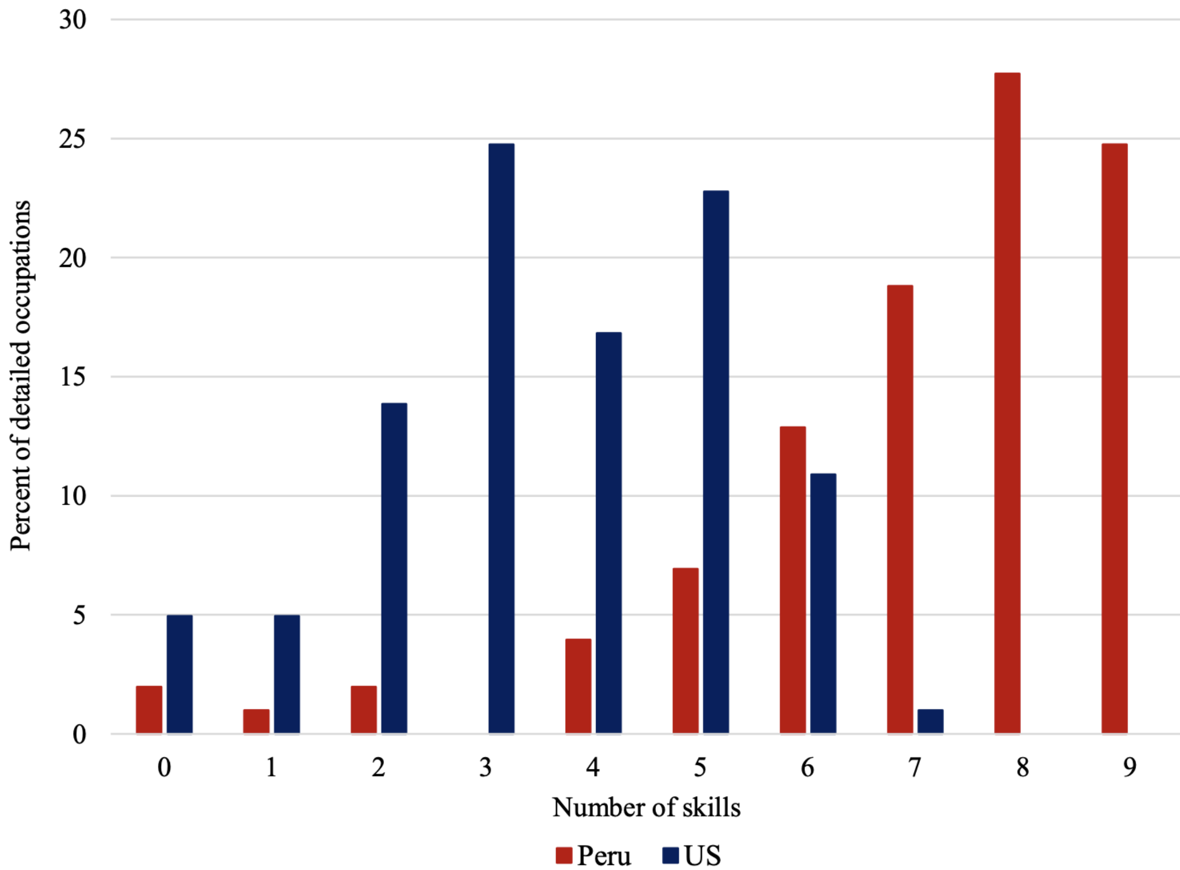
A well-functioning labor market is an essential component of economic development. The study of labor market dynamism, recruiting behavior, and skill outcomes in poor countries is an active research field. We contribute to it by designing and implementing an original survey on occupational skills and employers' recruiting efforts in Peru and the Southeastern US.

We provide three important findings. First, it is not necessarily the *mean* importance of occupational skills that differs between Peru and the US, it is its *distribution*. Peruvian jobs value and utilize a larger set of skills on average. Second, this flattening of the skill profiles is not due to a particularly ineffective nor obsolete hiring technology. Jobs fill quickly in Peru and firms use an equivalent mix of recruiting methods when compared to the US. Our third result derives from a model with uncertainty and complementarities in production: it highlights how differences in labor market institutions across countries can impact the stability of production and the demand for skills. In labor markets with higher turnover, it is optimal for establishments to avoid input specification and hire "toderos". We think this is an underappreciated insight that can expand the focus of poor countries' policy makers to encouraging specialization and long-term employment relationship, alongside much-needed labor reallocation.

Our paper documents the flatter occupational skill profiles in Peru and rules out some popular explanations, excess matching firctions and obsolete hiring technology, in favor of the effects of a turbulent labor market. We envision a fruitful path for future research in further exploring the connection between labor market institutions, labor reallocation and turnover rates, and equilibrium human capital accumulation in poor countries.

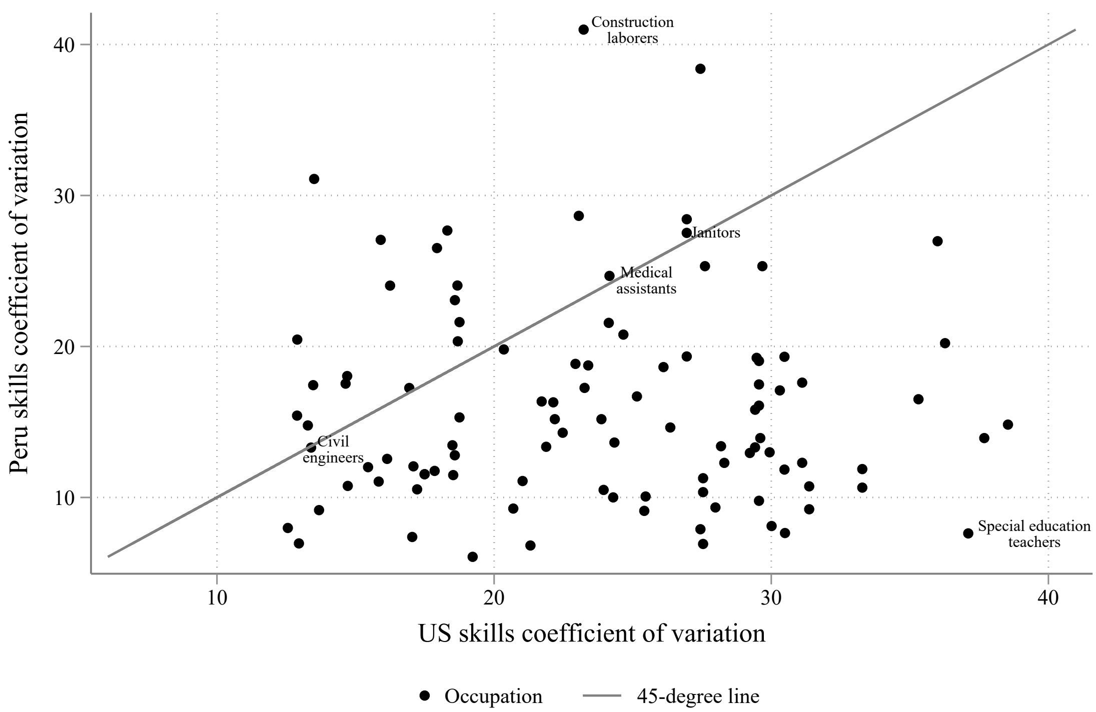
7 Figures and Tables

Figure 1: Peruvian jobs are more likely to report a larger number of important skills with respect to US jobs, and 18% of Peruvian jobs has all nine skill dimensions reported as at least “important”. The corresponding percentage for US jobs is zero.



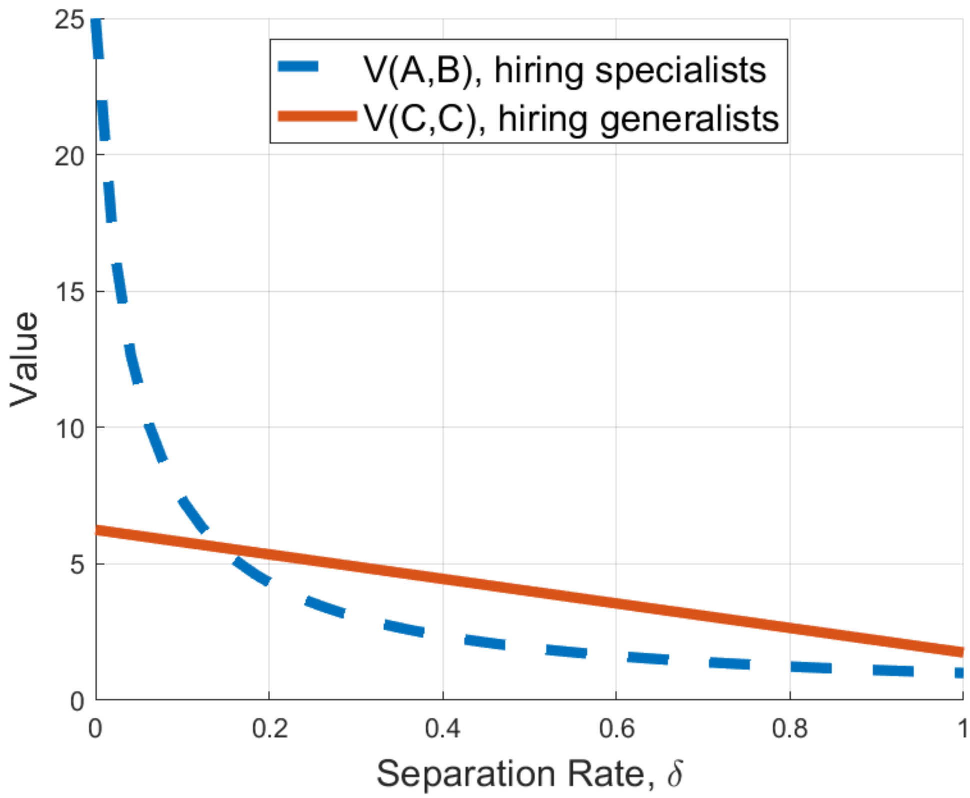
Note: Percentage of detailed occupations by number of skill dimensions that are reported as “important”, “very important”, or “extremely important” for Peru (red) and the US (blue). Source: SSERB-Peru and US O*NET 2017.

Figure 2: Most jobs in Peru have lower coefficients of variation and thus lower specialization than in the US.



Note: Within-occupation coefficient of variation for reported skill importance in each job's performance. Peruvian data is on the y-axis and US data on the x-axis. Source: SSERB-Peru and US O*NET 2017.

Figure 3: Hiring specialists becomes less and less attractive as job separations become more frequent.



Note: Numerical example of stylized model. Y-axis is value and x-axis is separation rate, δ. Source: Authors' calculations.

Table 1: Aggregate daily filling rate. The aggregate daily filling rate in Peru is 0.11, which implies that the aggregate vacancy duration is 9.1 days. This is about one-third of that in the US, according to JOLTS-DHI data. There is little evidence of excess time-to-fill frictions in Peru with respect to the US.

Expected start - posting date ("recruiting period")	% not filled by expected start date	% of jobs	Daily filling rate f^d
0-30 days	9	65.3	0.14
31-60 days	10	25.8	0.05
61-260 days	10	6.3	0.01
Aggregate	-	100	0.110

Notes: Percentage of vacancies not filled, distribution of realized matches, and daily job filling rate, by (expected) recruiting period length. Source: Authors' calculations based on SSERB-Peru.

Table 2: Recruiting methods in Peru and the US. Methods based on networks play an outsized role in recruiting in both countries. In general, there are only muted differences in how employers advertise their open positions and recruit candidates between Peru and the US.

	% of firms	
	SSERB Peru	SERB USA
Networks	*53.0*	*58.5*
Recommendations (friends and family)	30.8	38.7
Referrals from employees	42.3	43.2
Job posting	*47.5*	*50.5*
Job Boards (non-university)	32.3	–
Job Boards at universities	25.2	–
Others	*58.0*	*56.8*
Partnerships with universities	7.0	20.7
Social media	34.1	42.3
Traditional media	28.7	10.0
Job fairs	8.5	8.1
Mass recruitment campaigns	6.6	
Recall/rehire & staffing agencies	1.0	18.9
N	*994*	*111*

Notes: Percentage of firms using the given recruiting method as part of their recruiting strategy. The numbers in italics represent the percentage of firms using *at least one* of the recruiting methods in the corresponding group as part of their recruiting strategy. Source: Authors' calculations based on SSERB-Peru and SERB-USA.

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Appendix (for online publication only)

A 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 A 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 A.

The first two skills listed in table A 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.[18]

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 simple average importance reported by employers and employees in such occupations. 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 A), then averaged once again at the occupation level.

[18] "Basic computer skills" doesn't exist in O*NET as a stand-alone skill. We, therefore, omitted this category from our baseline comparisons. 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 A.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.

B Data

The survey of individuals only contains college-educated people, so our worker sample is heavily skewed towards more educated workers. However, we do not restrict the employers survey to firms that report information for jobs that require a college degree, or to firms that are matched with a college-educated worker. Specifically, the employers' survey is designed so that 50% of the firms are sampled purely based on the employment distribution in their province-sector-size cell. The remaining 50% of firms in the employers' survey are drawn from the sample of employers reported by respondents in the graduates' survey. This subsample creates a matched employer-employee dataset, and thus covers a random sample of firms in the urban provinces of Peru, stratified according to the provinces' working age population distribution. 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. Of the 500 firms in the matchable sample, only about 300 can be reliably matched with a worker in the graduates' survey. The discrepancy mostly arises from time discrepancies between the date of the firm interview (when the manager is asked about the firm's last hire) and the graduates' interview date (when the individual reports her current employer).

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	27.64
Graduated 1 year ago or sooner	30.60
Graduated between 1 and 2 years ago	37.14
Graduated 3 years ago or earlier	5.61
Exactly one job since graduation	44.71
At least one job since graduation	64.93
Self-employed since graduation	2.68
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		
1-10 employees	23.60	76.0
11-100 employees	47.90	20.0
100+ employees	28.40	4.0
Sector		
Services & Private Education	39.5	33.9
Wholesale and Retail Trade	17.0	45.09
Public Administration & Health	11.2	14.75
Construction	7.9	2.75
T&TLC	6.1	7.59
Manufacturing	5.0	7.97
Region		
Lima	65.9	46.0
Coastal (excl. Lima)	12.7	21.9
Mountain	20.1	24.4
Jungle	1.3	6.7
Observations	994	2,124,280

Notes: Distribution of firms across size, sector, and region. Source: Authors' calculations based on the SSERB-Peru and INEI micro-data for 2016.

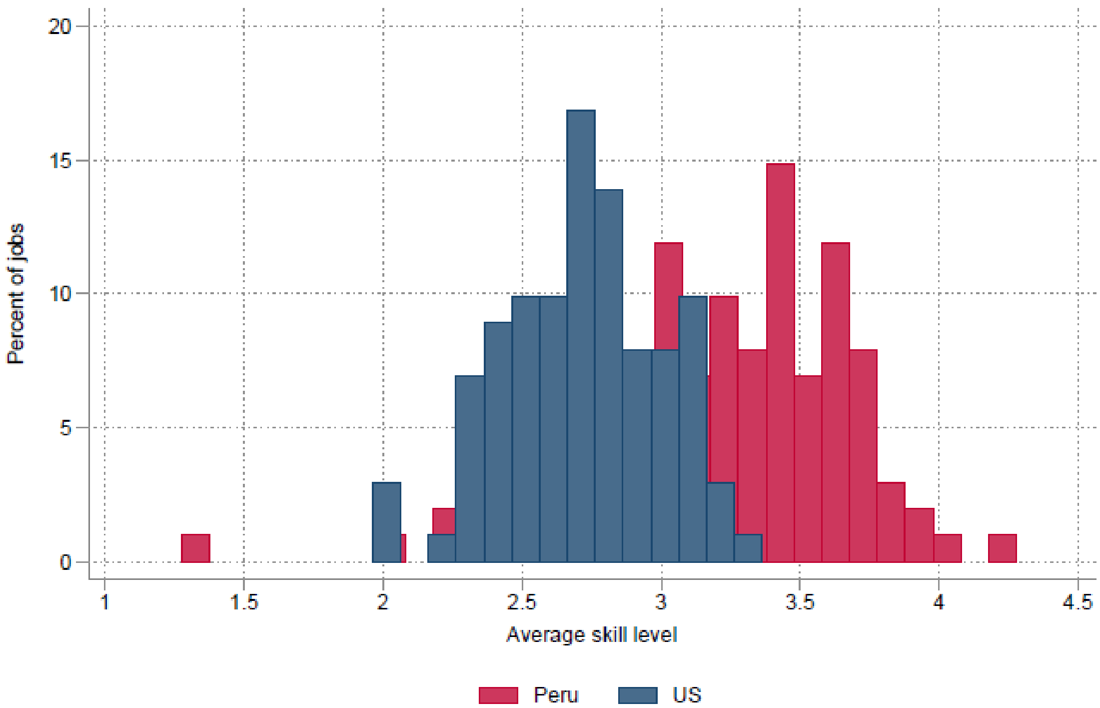
Table C.3: *Employers'* characteristics (SERB-USA)

	Sample	National$^{(i)}$
Size		
1-50 employees	34	75
51-500 employees	49	7
500+ employees	16	17
Sector		
Natural Resources, Construction & Utilities	6	10
Wholesale and Retail Trade, Hospitality	20	33
Professional Services	45	53
Manufacturing	29	4
Observations	299	7.912.405

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 U.S. Businesses Annual Datasets.

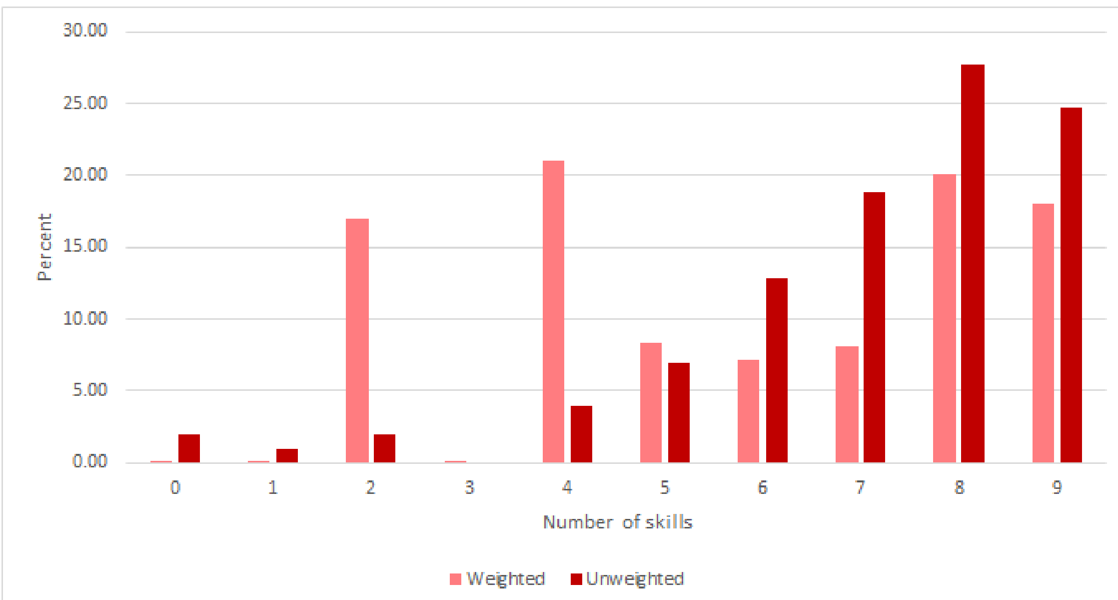
D Additional empirical results

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



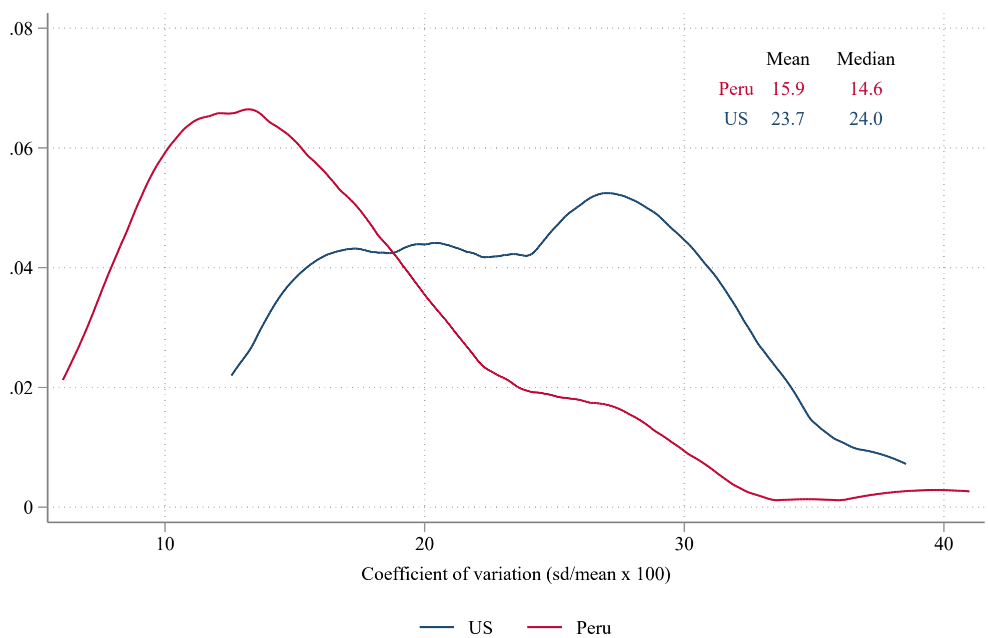
Note: Distribution of average within-occupation skill importance scores for Peru and the US. Source: SSERB-Peru and US O*NET 2017.

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



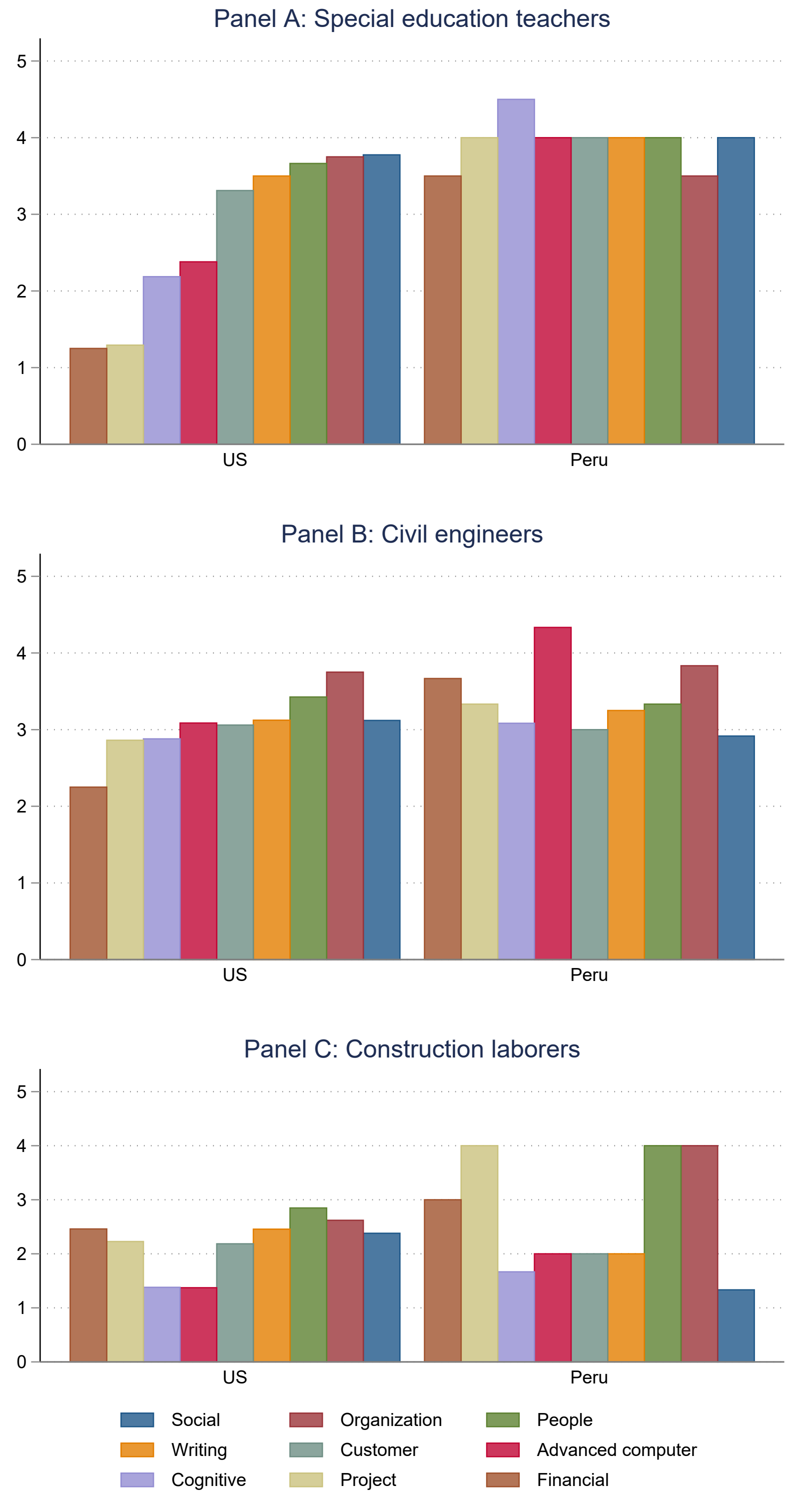
Note: Weights are constructed based on employment in narrow occupation-province cells, as computed from the Peruvian national household survey. Source: SSERB-Peru and ENAHO 2017.

Figure D.3: 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.



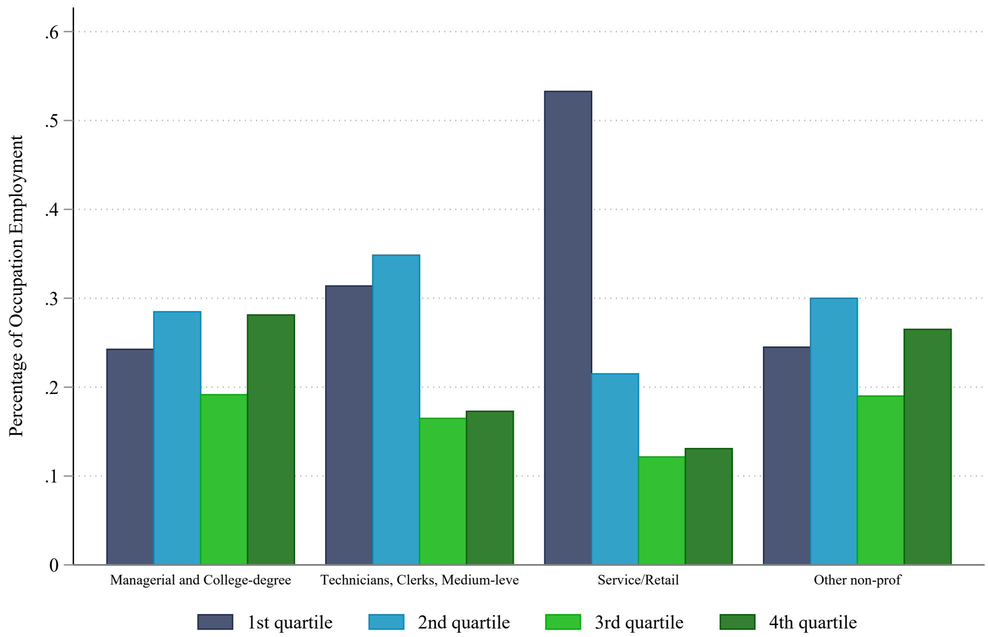
Note: Distribution of the within-occupational coefficient of variation for Peru and the US. Source: SSERB-Peru and US O*NET 2017.

Figure D.4: 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 are omitted from comparison as they are not directly measured in O*NET. Source: SSERB-Peru and O*NET 2017.

Figure D.5: 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 and ENAHO 2017.

E Proofs

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 $V(A, \centerdot) = V(\centerdot, B) = 0$ 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

$$V(C, C) = \omega^2 + \beta\left(\delta V(C, \centerdot) + (1 - \delta)V(C, C)\right)$$

where

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

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

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

and we obtain

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