The Skills of Rich and Poor Country Workers

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Abstract

What specific types of skills – e.g., scientific knowledge, math, or social skills – do workers raised in rich countries have that workers from poor countries lack? We investigate using information on occupation choices of immigrants. To an approximation, rich country workers are better at exactly those skills which are well-compensated in the U.S. economy, and in proportion to how well-compensated those skills are. Specifically, this means that rich country workers have the greatest advantages in skills related to the ability to generate new ideas (e.g., creativity and critical thinking), and that rich country workers' skills align especially closely with the skills used in management occupations. Lastly, we find that workers from rich countries are more varied in their skills (e.g., what one Canadian is good at is different from what another Canadian is). These findings do not appear to be accounted for by the non-randomness of immigration or mismeasurement of skills. Our results are consistent with the view that international differences in skills arise primarily in response to differences in demand for skills.

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1 Introduction

Countries vary enormously in their output per capita. Various evidence suggests that a substantial fraction of this cross-country variation in output – perhaps on the order of a half, though estimates vary – can be explained by differences in human capital (e.g., Hanushek and Kimko 2000, Hendricks 2002, Caselli 2005, Hsieh and Klenow 2010, Jones 2014, Manuelli and Seshadri 2014, Hendricks and Schoellman 2018).[1]

Given there exist differences in human capital, our paper asks a natural followup question: *What*, exactly, are workers from rich countries better at? Human capital is a vector of different competencies; for instance, Paul McCartney, Michael Jordan, and Bill Gates became wealthy thanks to very different kinds of skills. Evidence that skill is multidimensional includes comparative advantage in educational and occupational field choice (e.g., Paglin and Rufolo 1990, Kinsler and Pavan 2015, Kirkeboen et al. 2016, Guvenen et al. 2020, Lise and Postel-Vinay 2020); returns to experience which are specific to firms, industries, or occupations (e.g. Neal 1995, Dustmann and Meghir 2005, Kambourov and Manovskii 2009); imperfect correlations between directly measured competencies (e.g., Spearman 1904, Gardner 1983); and the independent predictive value of cognitive and non-cognitive skills for labor market outcomes (see Heckman 2008 for a review).

So, are workers from rich countries characterized by greater conscientiousness and diligence, perhaps reflecting cultural values about work? Are they better at cooperation? Are they better at abstract reasoning tasks? Are they distinguished by greater technical knowledge? Or something else?

While we believe this question is of intrinsic interest, the answer is also potentially informative about *why* rich countries have more human capital. Economists have proposed various explanations for cross-country differences in human capital production, such as quantity of schooling (e.g. Barro 1991, Mankiw, Romer, and Weil 1992; see Bils and Klenow 2000 for a critique), quality of schooling (Chiswick 1978, Bratsberg and Terrell 2002, Hanushek and Woessmann 2008, Hanushek and Woessmann 2012, Schoellman 2012), learning on the job (Lagakos et al. 2018a and 2018b), and cultural differences (e.g., Barro and McCleary 2003, Tabellini 2010, Fulford et al. 2020). Specific explanations generally imply something about what sort of skills should be different; for example, if cultural values related to taking work seriously are key, then we'd expect rich country workers to be more reliable and diligent.

To answer our question, we study the occupation choices of immigrants to the United States. A worker's occupation is a signal about their skills (Roy 1951); engineers are usually good at math, while journalists are typically good at writing. Using over one hundred measures of occupational skill requirements from O*NET, which we aggregate into 11 skill categories, we measure whether immigrants from high-income countries sort into occupations which require different skills than workers from low-income countries.

We have three primary findings.

[1]Differences in a Solow residual, reflecting factors such as technology and misallocation (Hsieh and Klenow 2009), seem to explain most of the remaining variation, with differences in physical capital being less important.

Our first, and most central, finding is that the skills which rich country workers specialize in are practically the same as the skills which differentiate high-income from low-income Americans – i.e., they specialize in skills which are well-compensated in the US economy. Of course, if rich country workers were better at everything, it would be expected that they would sort into whichever occupations pay the most, and would therefore use skills similar to high-earning Americans. But interestingly, this result holds true even after conditioning on income. That is, among immigrant workers with the same income, workers from rich countries work in occupations with skill requirements typical of higher-paid jobs. Furthermore, this single dimension almost exactly summarizes the skill differences; essentially, there are no differences in skill between rich and poor country workers except that rich country workers are better at the sort of skills which command high skill prices in the US economy.

The extent of alignment is notable, because, in a world with multidimensional skill, it is not *ex ante* obvious that the mix of skills produced by growing up in a rich country must align almost exactly with the skills which are rewarded in the marketplace in an advanced economy. For example, suppose that there were two skills rewarded in the marketplace, numeracy and literacy, and that rich countries had a human capital advantage only because their education system was better at producing numeracy; then high-earning individuals would be distinguished both by strong literacy and numeracy, while rich country workers would be distinguished only by numeracy.

Second, we find that rich country workers specialize most strongly in ideas – substantially more than they specialize in knowledge. By "ideas," we mean skills related to the generation of new thoughts or approaches. By "knowledge," we mean awareness of existing thoughts or approaches. Rich country workers have particularly large advantages in creativity and critical thinking, while differences in scientific knowledge, non-scientific knowledge, and understanding of equipment are much smaller.

Third, as an additional way to report our results, we characterize differences in skills by finding the occupation which best matches those differences in skills. So, for example, if we had found that rich countries specialize in skills related to math and detail-orientation but not physical strength, one might say "these are the sorts of skills that accountants use." In Section 3, we formalize a method to select the occupation which best fits our results.

We find that the best-fitting occupations are management occupations. That is, the greatest differences in skill between rich and poor country workers are among the sort of skills that managers use.

In Section 4, we consider possible reasons why our results might not accurately capture skill differences across origin countries, including that occupations may not reflect actual skill levels (e.g., due to licensing requirements), and that immigrants are non-randomly selected. We find evidence that these phenomena do bias our estimates – but that the effect of this bias is simply to attenuate our main results (i.e., skill differences are larger than measured) without influencing the relative rankings of which skills are important. Therefore, the takeaways described above still hold.

However, it is important to recognize that skills in our paper are defined as skills used in the United States (or, for one robustness check, Brazil). Someone who is good at verbal communication in Russia will not necessarily be good at verbal communication in the United States. Our results are based only on the skills which are used in the United States (e.g., ability to write well in English) as opposed to a broader definition of the same skill (e.g., ability to write well in one's native language).

While the main goal of our paper is simply to describe differences in skill, our results also speak to why countries differ in their production of human capital.

Our results are particularly consistent with the view that skill differences across countries arise because of differences in people's incentive to acquire skills. It is obvious that people acquire skills which are appropriate for their context: A hunter-gatherer might not do well in the labor market of New York City; yet, left alone in the woods in the middle of nowhere, the average New Yorker might not look so skilled compared with the hunter-gatherer. In a supply and demand framework, this explanation amounts to an argument that differences in skill quantities across countries are due to differences in countries' skill demand curves, as opposed to differences in skill supply curves.

This can explain why rich country workers happen to specialize in exactly the same skills which are well-rewarded in a rich country economy. (We verify that the American labor market especially rewards rich country skills by showing that immigrants with rich country skills have unusually large wage gains at migration.) By contrast, an explanation based on shifts in skill supply curves (i.e., if skill production varied for reasons unrelated to skill demand) would predict greater quantities to correspond with *lower* prices.

If this story is true, then differences in skills should also have some recognizable correspondence with differences in technology. We argue that each of our main findings has a connection with differences in technology previously documented in the literature. Difference in idea-producing skills are especially important in rich countries because (i) rich countries are closer to the technological frontier, and (ii) production is organized into larger firms (e.g., Tybout 2000, Poschke 2018), which increases the value of ideas to the innovating firm because ideas are non-rival (Schumpeter 1942). Managerial skill is also likely to be especially important in rich countries because production processes are more complex and involve the coordination of larger numbers of people playing specialized roles (Hidalgo and Hausmann 2009) – and, in fact, prior research specifically documents that technological differences are especially large for products requiring managerial talent to produce (Bahar et al. 2019).

As an additional test of this demand-based explanation, we hypothesize that workers from rich countries should be more specialized/varied in their strengths, since complex production processes require more specialized workers. We find that they are, using two approaches. First, we show that workers from rich countries have a higher variance of skill, conditioning on their income such that this has an interpretation of being specialized in different skills rather than reflecting variation in total skill accumulation. Second, we construct a definition of a "lopsided" occupation as being an occupation which has unusual skill requirements among similarly-paid occupations, and show that rich country workers work in more lopsided occupations.

We make three main contributions. First, we provide the richest description of precise skill differences between workers from high- and low-income countries. The most detailed prior description is by Schoellman (2010), who is primarily focused on the difference in skills between natives and immigrants but also notes some differences in a five-dimensional measure of skill between immigrants from high- and low-income countries. Second, we make methodological contributions, especially including the method of reporting skills with the match to the most similar occupation. We argue in Section 3 why this method has advantages compared to existing approaches which rely on researcher-selected aggregations of skills. Third, we contribute to the literature on understanding why countries differ in their human capital production.

The rest of the paper proceeds as follows. Section 2 describes our data sources. Section 3 describes differences in average skill. Section 4 describes robustness checks for these main results. In Section 5, we interpret our main results and describe results related to specialization. Section 6 concludes.

2 Data

Our main data source is the American Community Survey (ACS) over the years 2001-2017.[2] The ACS samples households in the United States who have lived at, or intend to live at, their current address for at least two months. This includes both US citizens and non-citizens. We define immigrants to be individuals who report a birthplace outside the United States, and we assign each immigrant to the country of their birth, e.g. people born in Peru are treated as Peruvians. In a limited number of cases, this will result in what is effectively a misclassification of country of origin, since some Peruvians will have actually spent most of their life, say, in Bolivia.

Our primary analyses restricts to immigrants between the ages of 25 and 60 who immigrated within the last five years.[3] This limits our sample to people whose skill levels have presumably been driven by their origin country environment. Our analyses are also restricted to individuals who report an occupation and positive income.

We measure birth country GDP per capita PPP using World Bank data. Our primary specifications use GDP per capita in the year that the individual is observed in the ACS, with year dummies absorbing any bias that would arise from comparing earlier to later years of data, but our results are not sensitive to assigning every country a GDP per capita from a fixed year. For a handful of countries, GDP per capita is not available in all years and must be imputed, but the

[2] We use data provided through IPUMS USA (Ruggles et al. 2020).

[3] The ACS asks respondents what year they "came to live in the United States." If they have immigrated more than once, the most recent year is reported.

Table 1: Descriptive statistics

Age (mean)	36.00
Age (SD)	8.66
Wage and salary income (mean)	40,013.50
Wage and salary income (SD)	52,162.54
East Asia & Pacific (mean)	0.22
Europe & Central Asia (mean)	0.14
Latin America & Caribbean (mean)	0.41
Middle East & North Africa (mean)	0.04
North America (mean)	0.03
South Asia (mean)	0.14
Sub-Saharan Africa (mean)	0.05

Note.- Summary statistics for primary sample (ages 25-60, immigrated in the last five years). $N = 255,494$. Region variables are dummy variables equal to one if the immigrant's origin country is in that World Bank region.

method of imputation does not affect our results.[4]

Consistent with the previous literature (e.g., Hendricks 2002, Hendricks and Schoellman 2018), we find that earnings in the US are higher for immigrants from higher-income countries. A regression of the average log income of immigrants from a country on the origin country's log GDP per capita gives a coefficient of 0.231, with standard error of 0.026.[5]

We measure the skill requirements of each occupation using data from the Occupational Information Network (O*NET). O*NET is a United States Department of Labor database designed for job-seekers which describes occupations using a list of over one hundred characteristics describing the type of work performed and the skills and qualifications required to work in that occupation. We focus on occupation characteristics listed under the categories *Skills*, *Abilities*, *Knowledge*, and *Work Styles*. For some of these categories, O*NET provides both a level of skill required and an importance of a skill; we use the importance measure for our primary results, but the results are effectively identical using the level measure instead. This produces a list of 136 characteristics. For simplicity, we will refer to these characteristics as "skills." The full list of skills can be seen in our results in Appendix B.

Next, we aggregate these 136 characteristics into indices. Based on the definitions of the

[4]In some cases information for year 2017 was not available and the latest update available in the World bank database was used. For the countries of Syria (2010), Cuba (2010), Venezuela (2014), Bermuda (2013), and Eritrea (2011), we use the values for the years in parentheses and the year before to calculate a growth rate to then estimate a 2017 approximate value for GDP per capita. Particularly for Cuba and Syria we use information from 2010 from FRED (https://fred.stlouisfed.org/series/RGDPCHCUA625NUPN) because information was not available from the World Bank. For Czechoslovakia, Yugoslavia, and the USSR, all of which no longer exist, we used the population-weighted mean for the countries which have replaced them (e.g., the Czech Republic and Slovakia for Czechoslovakia). Individuals born in England, Scotland, Wales, and Northern Ireland were assigned the United Kingdom measurement of GDP.

[5]Observations are a country in an ACS survey year, giving 1,826 observations. We control for survey year dummies and cluster at the country level. The income variable used here, and in the rest of the paper, is individual wage/salary income.

characteristics, we are able to assign almost all O*NET skills to one of the following 11 broader categories of skill:

1. **Creativity:** The ability to generate new ideas.
2. **Critical Thinking:** The ability to synthesize information or evaluate ideas, especially in open-ended contexts.
3. **Effort:** Whether the worker is reliable, organized, and works hard.
4. **Language:** Skill in reading, writing, and oral communication.
5. **Math:** Mathematical skill.
6. **Social:** Skills related to the ability to get along with others; people skills.
7. **Technology:** Knowledge and abilities specifically related to the use or maintenance of complex/advanced equipment (e.g., planes, computers, machinery).
8. **Scientific Knowledge:** Knowledge of basic science (e.g., of physics, chemistry, or biology).
9. **Other Knowledge:** Knowledge not captured under Technology or Scientific Knowledge – e.g., of law, business practices, or the humanities.
10. **Other Cognitive:** Skills related to basic cognitive functions – e.g., reaction time, memorization, spatial visualization, and ability to avoid distraction.
11. **Physical:** Strength, endurance, and dexterity.

The exact list of skills used in each index is given in Appendix A. We judge that 13 of the 136 skills do not fit well within any of these categories; we keep these for the skill-level analyses but they are not used for the index-level analyses. To construct indices from the individual skills, we first normalize each individual skill within our merged data (see below), then sum over all skills within an index, then normalize this sum.

We merge O*NET data to ACS data on the basis of occupation. In the ACS data, many observations are missing the final digit(s) of the occupation code, which is generally 6 digits long. Because occupation codes are hierarchical, occupations sharing the first 4 or 5 digits generally have very similar skill requirements, so we impute skill values based on the average among occupations sharing the same non-missing digits. The occupation codes used are not consistent across data sets, so some crosswalking is required. Finally, we drop observations with military occupations, for which O*NET does not assign skill requirements; this affects .2% of our primary sample.

2.1 Income-conditional skills

Many of our regressions use income-conditional skill measures as the dependent variable. To construct these, we first bin workers into deciles of income. Then, among workers within each decile, we estimate the mean and standard deviation of each skill s, and construct the income-conditional level of skill s as the number of standard deviations above or below the average.

The reason for using this outcome measure is that, when we use skill usage without conditioning on income, our results might be biased in the direction of suggesting that more skilled workers are specialized in whatever it is that commands higher earnings in the US economy. This is because workers will presumably sort to occupations which pay them more; if workers from rich countries were more skilled at everything, then their advantage would appear to lie in whatever skills are used by higher-paying jobs.

Imagine, for example, that there are two types of skill: physical and cognitive. Suppose in addition that there are two occupations, H and L, where H requires 2 units of cognitive skill and 1 unit of physical skill and pays a wage of 2, while L requires 1 unit of each and pays a wage of 1. Lastly, suppose that workers from rich countries have 2 units of each skill and workers from poor countries have 1 unit of each skill. If workers choose the occupation which will pay them the most, then workers from rich countries will sort into occupation H because it pays more, while workers from poor countries will sort into L because they do not satisfy the skill requirement for H. Therefore, measuring skill using occupations would erroneously imply that rich country workers have an advantage only in cognitive skill but not in physical skill. In reality, this would simply reflect that the higher-paying job has a higher cognitive skill requirement. If H had required 1 unit of cognitive skill and 2 units of physical skill instead, the implication from the data would be that rich country workers were better at physical skill.

This problem can be addressed by comparing skill usage among workers who earn the same amount. Imagine an economy in which all individuals select an occupation solely to maximize their earnings. Then, comparing individuals i and j who are paid the same but work in jobs with different skill requirements, we can reasonably suppose that i would earn (weakly) less than j if i tried to work in j's occupation, and similarly for if j tried to work in i's occupation. Differences in skill requirements therefore reflect differences in skill: i must be better at the things which i's job requires but j's job does not.

A simple model may help readers understand the interpretation of income-conditional skills measures. Suppose that there are two skills, A and B, with worker i's income being

$$y_i = h(a_i, b_i)$$

for some function h which is strictly increasing in both of its arguments. We can think of A as being a skill of interest, and B being its complement in an earnings function, potentially including random luck in the labor market in addition to actual skills.

If workers i and j have the same income (i.e., $y_i = y_j$), but $a_j > a_i$, then it must be that $b_j < b_i$. Figure 1 illustrates graphically; among workers on the same "iso-income" (collection of skill bundles delivering the same income), those who have higher value of A must have lower values of B.

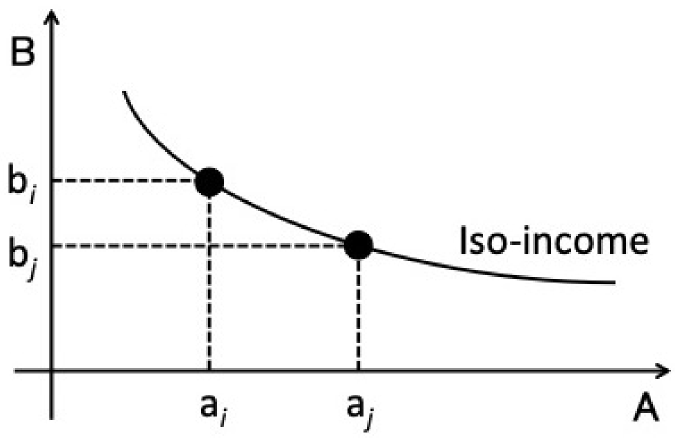


Figure 1: Illustration

Let p_i^A be the percentile of worker i's level of skill A among workers with the same income, and p_i^B be the analogous percentile for skill B. Then $p_i^B = 1 - p_i^A$, because h is increasing in each of its arguments. Therefore, any intervention which increases the expectation $E(p_i^A)$ will decrease $E(p_i^B)$ by the identical amount.

In this respect, we can think of income-conditional skills as measuring a relative advantage in some skill, or a skill bias. Increases in B alone will reduce an individual's place in the income-conditional distribution of A. Furthermore, this skill bias is measured relative to the composition of skills which generally distinguish high earners from low earners; see examples below.

As we discuss in Section 4, the units of skill measures are largely arbitrary. However, suppose that the distribution of income-conditional A for workers from country c first-order stochastic dominates the distribution of income-conditional A for workers from country c'. Then, for any A' and B' which are increasing transformations of the units of A and B respectively (i.e., which preserve the ranking of which workers are more skilled than which others for each skill), workers from country c will have higher average income-conditional values of A', while workers from country c' will have higher average income-conditional values of B'. Therefore a key target for our robustness checks will be to check for evidence of first-order stochastic dominance of income-conditional skills, since this implies that our results are not driven by the choice of units for skills.

Examples To develop intuition about how income-conditional skills work, consider the following simple models.

Example 1. Suppose that individual i's earnings y_i are produced from their skill levels a_i and b_i by

$$y_i = a_i + b_i.$$

Suppose that A and B are drawn independently from normal distributions with mean of 10 and standard deviation of 1. Next, 10% of observations receive an intervention which increases their

a_i by .1 and b_i by .3.

Regressing A and B on a dummy for receiving the intervention, D, gives coefficients of .1 and .3, respectively. But, binning observations by income first and regressing income-conditional skills Z^A and Z^B on D, we instead obtain coefficients of $-.14$ and .14, respectively.[6] This reflects the fact that, while the intervention increased both A and B, it increased B by more, so that people who were treated with the intervention are on balance more specialized in B.

Example 2. Suppose that the data-generating process is exactly as above, except that

$$y_i = .1a_i + b_i,$$

i.e. skill A is nearly irrelevant to income. Now, when regressing Z^A and Z^B on D, we instead obtain coefficients of approximately .07 and $-.07$, respectively. That is, the intervention increases income-conditional A. Intuitively, this is because high earners in general are very specialized in B (due to the fact that A is almost irrelevant to income), while the intervention produces only a somewhat larger effect on B than on A. The income-conditional skills measure asks whether individuals with $D = 1$ are more specialized in skill A than are high earners in general; and the answer is yes, because high earners are simply not very specialized in skill A.

The examples illustrated the following key points. First, income-conditional skills capture specialization in skills. Second, income-conditional skills capture this specialization *relative to the degree of specialization of higher-earning individuals in general.* Interventions which produce the same mix of skills as is typical among higher earners will not produce any effect on income-conditional skills. But interventions which produce skill in any other proportion will tend to affect income-conditional skills.

In particular, Example 2 illustrates that conditioning on income will tend to highlight increases in precisely those skills which have low skill prices. In this respect, the measure is geared to find precisely what (in Section 3) we nonetheless *don't* find: any meaningful differences in any skills which aren't highly compensated in the American economy.

3 Results

We begin by constructing skills and skill indices (both income-conditional and unconditional) for each worker in our primary sample. We then aggregate these measures by taking averages at the country-year level (e.g., an observation might be immigrants from Mexico observed in the 2014 ACS).[7]

Let the average level of skill s for country c in year t be called $\bar{Z}^s_{ct}$. Furthermore, let $zGDP_{ct}$ be country c's output per capita, in units of number of standard deviations above or below the average of log of output per capita in that year. (For reference, one standard deviation of log

[6] These values are measured via simulation with 20,000,000 observations and 500 bins of income.

[7] We drop countries with fewer than 20 total individuals observed.

of output per capita is equal to 0.82). For each skill s, we then regress $\bar{Z}^s_{ct}$ on the standardized natural log of national GDP (denoted $zGDP_{ct}$) and ACS year dummies (γ^s_t):

$$\bar{Z}^s_{ct} = \beta^s zGDP_{ct} + \gamma^s_t + \epsilon^s_{ct}.$$

Standard errors are clustered by country.

Table 2 reports results for the skill indices under four possible versions of this regression. Complete results for every O*NET skill are reported in Appendix B. The first two columns of Table 2 report results using unconditional skills, while the third and fourth columns report results using income-conditional skills. Additionally, to help compensate for the non-randomness of the immigration decision (which we return to in Section 4), the second and fourth columns construct average skills of immigrants from country c by weighting individuals to match the distribution of educational attainment in their origin country as estimated by Barro and Lee (2013).

Rows are ordered by the coefficient in the last column (income-conditional and reweighted), which we consider to be our preferred estimates.

The results show that there are broad differences in skill, with either all or all but one skill category significant in every specification. Across the four versions of our results, the largest coefficients are for Communication, Creativity, and Critical Thinking. However, Other Knowledge, Math, and Effort have coefficients which are not much smaller.

Among the three categories with the largest coefficients, the results for Communication are possibly related to language barriers, and therefore we have less confidence that this reflects skill differences that can account for differences in GDP per capita in the origin country. The other two largest coefficients, for Creativity and Critical Thinking, are related to the generation and evaluation of ideas. Cognitive work can involve either the ability to produce and evaluate new ideas, as among the variables just mentioned; or it can involve awareness of existing ideas and information, as suggested by the commonly-used term "knowledge economy."[8] Knowledge seems less important for differentiating workers from rich and poor country workers; the coefficients for Other Knowledge are not far behind those for Creativity and Critical Thinking, but the coefficients on Scientific Knowledge are substantially smaller, as are the coefficients for Technology (which in significant part reflects knowledge of advanced equipment).

The coefficients for Effort and Social are positive but smaller than the top cognitive skills described above. This is consistent with human capital differences being driven in some part by purely cultural factors such as attitudes about work or ability to work in teams, but seems unlikely if those were the most essential factors directly responsible for differences in productivity.

Table 2 also shows that the estimates are not particularly sensitive to reweighting. This is in part because there are canceling effects of reweighting: Immigrants from poor countries are more

[8]Our distinction between ideas and knowledge is related to, but not necessarily the same as, psychologists' distinction between fluid and crystallized intelligence (Cantrell 1992). "Crystallized" intelligence is the ability to draw conclusions based on existing knowledge and experience, while "fluid" intelligence is the ability to reason about novel situations without relying on existing knowledge or experience. The skills we describe as ideas skills seem more closely related to fluid intelligence. However, we lack any psychometric data to confirm this connection.

Table 2: Main results

	Unconditional		Income-conditional	
Skill index	Baseline	Reweighted	Baseline	Reweighted
Communication	0.228	0.217	0.142	0.134
	(0.021)	(0.026)	(0.017)	(0.022)
Creativity	0.250	0.214	0.145	0.124
	(0.019)	(0.021)	(0.012)	(0.015)
Critical Thinking	0.251	0.216	0.142	0.118
	(0.021)	(0.023)	(0.015)	(0.018)
Other Knowledge	0.160	0.149	0.118	0.111
	(0.017)	(0.021)	(0.015)	(0.018)
Math	0.207	0.191	0.113	0.108
	(0.018)	(0.019)	(0.014)	(0.017)
Effort	0.178	0.174	0.097	0.098
	(0.019)	(0.025)	(0.015)	(0.021)
Social	0.111	0.128	0.060	0.083
	(0.018)	(0.025)	(0.016)	(0.023)
Other Cognitive	0.069	0.110	0.023	0.063
	(0.009)	(0.013)	(0.008)	(0.012)
Scientific Knowledge	0.130	0.097	0.074	0.047
	(0.012)	(0.014)	(0.010)	(0.012)
Technology	-0.024	0.000	-0.022	0.002
	(0.012)	(0.017)	(0.011)	(0.017)
Physical	-0.187	-0.149	-0.100	-0.074
	(0.019)	(0.022)	(0.014)	(0.018)

Note.- List of the index skills coefficients from a regression of skill index usage (in standard deviations) on log of GDP per capita (in standard deviations), controlling for survey year fixed effects. Columns (1) and (2) present the results using unconditional skills, while columns (3) and (4) present the income-conditional skills indices. Columns (2) and (4) are the results weighted using the Barro-Lee weights. For the skill indices definition, see Appendix A. Baseline: $N = 2,212$; Weighted: $N = 1,826$. Robust standard errors clustered at the country level in parentheses.

selected on the basis of education, but the skills-education gradient is steeper among workers from rich countries. Because coefficients are very similar for several skill indices, reweighting affects the exact ranking of the indices. However, there is a very strong correlation between results with and without reweighting: At the level of individual skills (i.e., without aggregating to indices), there is a correlation of .99 between the baseline and reweighted estimates for unconditional skills, and a correlation of .98 between the baseline and reweighted estimates for income-conditional skills. Aggregating to indices, these correlations are .99 and .97, respectively.

Alternative specifications Our results are not sensitive to various changes in specification.

Because our results could be influenced by a correlation between origin country GDP per capita and age at time of immigration, we replaced income-conditional skills with income-conditional skills residualized on age and age squared before taking national averages. The results produced in this way are so indistinguishable from our main results as to be effectively identical: Across all skills, the correlation between $\widehat{\beta}_1^s$ with these controls and $\widehat{\beta}_1^s$ without them is greater than 0.99.

Similarly, our results are not sensitive to the number of bins of income used to construct income-conditional skills. We obtain effectively identical results across a range of number of bins of income, or when residualizing skills on log income within each bin prior to standardizing and taking country averages.

Aggregating to an average income-conditional skill level for each country across all years (as opposed to by year of the ACS) and using a single value of log GDP per capita for each country (created by averaging over all years of log GDP) produces results which are also virtually identical to our main results (correlation of 0.99).

Adding a control for the origin country's region in our main regression gives results which have a correlation of 0.98 with our main results.[9]

For skills where both a level and importance of a skill are available in the O*NET data, our main results are based on the importance measure. The correlation between our main results and the results using the level measure instead is 0.98.

Finally, we imputed GDP per capita for some country-years, due either to missing World Bank data (e.g. because of war in Syria) or because of changing national boundaries (e.g. some respondents list Czechoslovakia as their country of birth). We again obtain effectively identical results dropping any or all of these countries.

3.1 Closest occupation

The results reported in Table 2 rely on our subjective choices of how to aggregate skills into indices. We next consider a way to report our full results across all skills which does not rely on our subjective choices.

In particular, we next report skill differences in terms of a closest occupation. Suppose that we had found that workers from rich countries had the greatest advantage in mathematical skills

[9] We use the World Bank classification of regions.

and attention to detail. Then one might say "these are the sorts of skills that accountants use." By contrast, if workers from rich countries had their greatest advantage in persuasiveness and verbal communication, one might say "these are the kinds of skills that marketers use." The procedure below finds the occupation which is the closest fit to the sort of skills for which we observe rich country workers to have the greatest advantage.

This approach has the advantages that (i) it captures information about the full range of over 100 skills for which we have data, yet (ii) it is relatively "nonparametric" (figuratively speaking), in the sense that the model is not constrained to choose from a very small number of possible results which are pre-imposed by researcher choices,[10] while (iii) it nonetheless produces a result which is simple and interpretable, since most people have a sense of the skills required by most occupations.

Note that, just as our preferred results use income-conditional skills, we will define an occupation's skills in terms of that occupation's *income-conditional* skill requirement, i.e. what distinguishes workers in that occupation from workers with a comparable overall level of income.

The procedure is as follows. For each occupation j, we construct the average income-conditional skill of immigrants workers in occupation j.[11] Let Occ_j^s be this average for skill s. Similarly, our preferred results above (income-conditional, reweighted specification) produce an estimated coefficient $\widehat{\beta}^s$ for each skill s. We select the nearest-fitting occupation j and a scalar multiple λ to solve the following minimization problem:

$$\min_{\lambda \geq 0, j} \sum_s \left(\widehat{\beta}^s - \lambda Occ_j^s \right)^2 .$$

The expression to be minimized would be the smallest possible, for example, if Occ_j^s were exactly a positive scalar multiple of β^s.

The choice of j can be interpreted as "the set of skills here are the sort of skills used by people in occupation j," while λ describes an intensity, with larger λ indicating a stronger magnitude of skill bias in the direction of the sort of skills used in the selected occupation. We constrain λ to be positive such that we are looking for occupations which resemble rich country workers' skills.

We solve this minimization problem in two steps. First, for each occupation j, we find the λ_j that minimizes the expression

$$\sum_s \left(\widehat{\beta}^s - \lambda_j Occ_j^s \right)^2 .$$

This can be done simply by regressing $\widehat{\beta}^s$ on Occ_j^s while omitting the constant, where an observation in this regression is a skill s. The resulting coefficient on Occ_j^s is the best-fitting λ_j. We constrain to $\lambda_j \geq 0$ by dropping occupations with negative λ_j, but this constraint is not binding for the best-fitting occupations.

[10]This agnosticism might be a disadvantage in a context where the researcher has more specific hypotheses to investigate, but is advantageous in a context like ours where the primary goal of our empirical exercise is exploratory and descriptive.

[11]As before, income-conditional skills are in units of standard deviations above or below the average. Occupations are defined as unique O*NET occupation codes, which can sometimes correspond to multiple occupations in the ACS occupation codes.

Table 3: Best-matching occupations

Occ. code	Occ. name	$\widehat{\lambda_j}$	R-squared
11-101	Chief executives	0.072	0.72
11-919	Managers, all other	0.116	0.71
13-108	Logisticians	0.075	0.64
13-111	Management analysts	0.063	0.62
25-101	Postsecondary teachers	0.058	0.62

Note.- List of the five O*NET occupations with best fit (highest r-squared) to the main results (estimates of β^s from specifications using income-conditional with educational reweighting). $\widehat{\lambda_j}$ is the estimated value of λ_j. See text for details.

Second, we select the j which minimizes the objective function, given we know from the first step what λ_j would be. This can be done simply by noting the R-squared of the above regression for each occupation j, and selecting the j with the highest R-squared.[12]

Table 3 reports the top five occupations which minimize this squared error, along with the best-fitting λ_j for that occupation and the r-squared of the regression.

The results suggest that the skills of rich country workers can be said be most like the skills of managerial workers. The best-fitting occupation is Chief Executives, and the next-best fits are also closely related with business management.

The R-squared tells us how closely this description matches the full set of skill biases. The R-squared of 0.72 means that the description that "the skill bias here is in the direction of Chief Executives' skills" fits our results to a substantial extent. In particular, there is a correlation of $0.72^{1/2} = 0.85$ between our main results and the income-conditional skills of Chief Executives.

3.2 Correlation with high-earners' skills

The skills of rich country workers that we obtain from our main results also closely resemble the skills of high-earning workers in general. To demonstrate this, we estimate the regression

$$Z_{it}^s = \alpha^s Inc_{it} + \xi_t^s + \nu_{it}^s,$$

where i denotes an individual, t denotes a survey year, Z_{it}^s is the number of standard deviations above or below the average that the individual is for their occupational skill usage (relative to the entire sample in that year, i.e. not income-conditional), Inc_{it} is the respondent's income, and ξ_t^s represents ACS year dummies. To avoid mechanical correlation with our main results, we restrict this regression to native-born workers between the ages of 25 and 60, i.e. not including anyone

[12]Choosing the occupation with the highest R-squared gives the minimum of the objective function because, across all j, the variation in β_s to be explained is the same. Therefore, the occupation j which explains the greatest fraction of variation in β_s will also have the smallest sum of squared residuals.

used in our main analysis.[13]

The results are very strongly correlated with our preferred results: The correlation between our estimates $\widehat{\alpha^s}$ and $\widehat{\beta^s}$ is 0.91. As would be expected, the correlation is even stronger without conditioning on income: 0.95 for reweighted unconditional skills.

That is, the skills which differentiate rich country workers from poor country workers – even conditional on earning the same amount – closely resemble the skills which differentiate high-earning natives from low-earning natives.

We discuss in Section 2 why using income-conditional skills should highlight differences in skills with low skill prices, i.e. why this sort of analysis should be conservative. However, it is also important to note one potential contributing factor to this result, which is the role of luck in earnings. It has long been known that workers' earnings seem to be driven in part by factors unrelated to their skill or productivity (Slichter 1950). Suppose there is some difference between how much someone makes and how much they might have been expected to make based on their level of skill; call this difference *luck*. High earners will be on average more lucky than low earners, for the reason that luck increases earnings. If rich country workers are not more lucky than poor country workers, but have higher earnings due to differences in skills, then they will tend to have low income-conditional luck. Because they have low income-conditional luck, it follows that they must have high income-conditional skill (see the model in Section 2). This may help explain why most estimates $\widehat{\beta^s}$ are positive, and may contribute to the alignment of $\widehat{\beta^s}$ with $\widehat{\alpha^s}$.

4 Robustness

The previous section describes differences in occupational skill usage between immigrants to the US from rich and poor countries. A natural question is whether this accurately describes differences in skills of workers who remain in the origin countries.

There are two central issues which might lead our measurements to not reflect differences in skills between workers from rich and poor countries generally. The first is that we might mismeasure workers' skills. The second is that, even if we successfully describe differences in immigrants' skills, these differences might be due to the non-randomness of immigration rather than differences in the skill levels of origin country populations.

4.1 Measurement error in skills

There are three primary concerns about mismeasurement of skills. The first is about whether measures of skill are context-specific, e.g. whether someone is good at communication might depend on who they are supposed to communicate with. The second is that our measure of skills is noisy, e.g. since workers within the same occupation do not have identical levels of skill. The third is that the units of skill measurements are arbitrary. We discuss each of these in turn.

[13]Mechanical correlation would arise because individual workers from rich countries earn more on average than workers from poor countries. For computational reasons, we also estimate this regression using a random 10% subsample.

Location-specific skills Skills are to some extent location-specific. For example, in the US, verbal communication effectively means the ability to communicate in English. This is a less important skill in, say, Japan; there, ability to communicate in Japanese is more important. To the extent that we measure differences in verbal communication by nation of origin, it is therefore unclear whether this reflects differences in general communication ability (e.g. the carefulness with which people organize their thoughts) or whether it simply reflects the extent to which the communication skills required in a worker's origin country are aligned with the communication skills needed in the US.

This problem of skill transferability is a source of measurement error to the extent that a variable labeled as "verbal communication" would not reflect the relevant notion of verbal communication for understanding output in non-US contexts. But this is not a source of measurement error if we conceive of skills as being the US versions of the measured skills. Therefore, our results should be interpreted as reflecting differences in the US versions of the measured skills.

One way to assess whether language barriers in particular are important for the interpretation of our results is to restrict our sample to immigrants who report either that they speak only English or that they speak English very well. At the level of individual skills (i.e., without aggregating to indices), the correlations between the results with and without this sample restriction are .97 and .93 for the baseline and reweighted income-conditional skills results, respectively, and .94 and .92 for the baseline and reweighted unconditional skills results, respectively. Furthermore, replicating our main conclusion from Section 3.2, the correlation between $\widehat{\alpha}^s$ and the value of $\widehat{\beta}^s$ obtained from this subsample is NUMBER. In short, our main results appear not to be driven by differences in occupational sorting due to English proficiency.[14]

Occupation as imperfect skill proxy Workers in the same occupation do not have identical skill levels; therefore, occupation cannot possibly be an exact measure of skill (e.g., Deming and Kahn 2018).

Our results would be biased if the measurement error from using occupation as a proxy for skills is correlated with output per capita of an immigrant's origin country. Examples of mechanisms which might create such systematic correlation are licensing requirements which are easier to satisfy for immigrants from rich countries; a tendency for immigrants from low-income countries to have a lower threshold to accepting a job, due to liquidity constraints, that might lead them to incorrectly appear low-skilled in the data; employer discrimination in screening applicants (Oreopoulos 2011); or clustering in certain occupations arising due to social networks in job search rather than match quality, especially among low-skill occupations (e.g., Waldinger 1994, Patel and Vella 2013).

We have three robustness checks to assess whether these mechanisms are likely to meaningfully influence our results.

First, we consider whether licensing requirements might explain our results. For this to be the

[14]Additionally including those who "speak English well" does not change the conclusion.

case, it must be that workers from some countries find it easier to work in licensed occupations, and that licensed occupations require systematically different skills.

If this were true, we would imagine that origin country GDP per capita would predict licensing. Using CPS data, we construct the fraction of workers in a given occupation who report that their job requires licensing. We code an occupation an licensed if more than 10% of workers in that occupation in the CPS report requiring licensing.[15] In our main ACS data, we then merge this information to workers on the basis of their occupation, and compute the fraction of workers from each origin country in each ACS survey year who work in a licensed occupation. Regressing this on $zGDP_{ct}$ with year dummies and clustering by country, we obtain a coefficient of $-.009$ with a standard error of .005, which is significant at the 10% level. In other words, the rate at which workers from rich and poor countries work in licensed occupations is, while perhaps not literally identical, at least extremely similar in our data.

Furthermore, if our main results were substantially driven by licensing, we would expect them to be closely aligned with skills used in licensed occupations. Instead, there is only a moderate relationship. For each skill s, with occupations as observations, we regress the usage of skill s in occupation j on a dummy for whether occupation j is licensed or not, as defined above. This produces a regression coefficient for each skill s. Then we take the correlation between these coefficients and our main results. This correlation is .20. That is, licensed occupations do, to some extent, use skills similar to our main results; however, the correlation is moderate.

We conclude that it is unlikely that licensing requirements are important in explaining our main results.

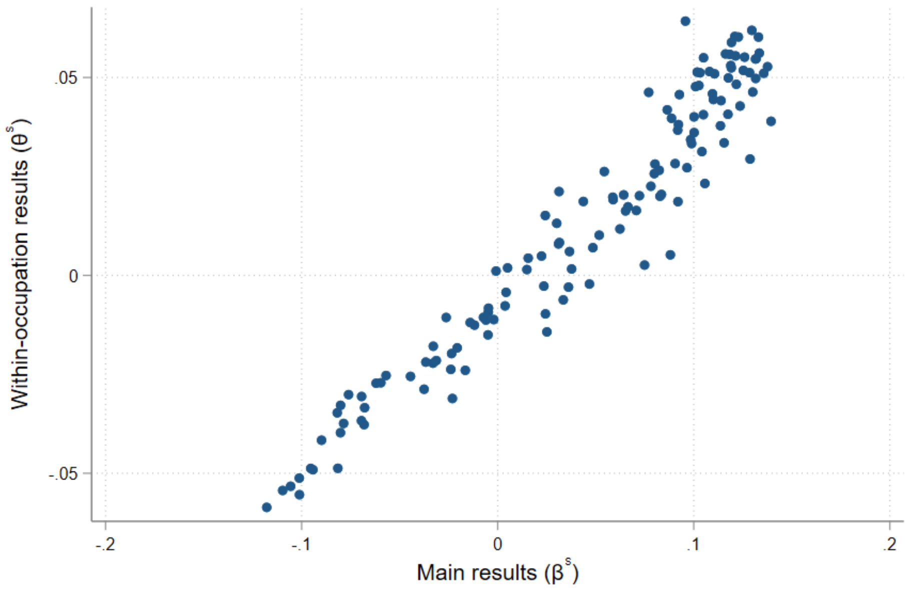
Second, we assess whether job search might influence our results. We do this by looking at results slightly later after immigration, on the principle that job search (especially the role of liquidity constraints) will be the most important in the period directly after immigrating. Restricting to the sample of immigrants who arrived in the US between 2 and 5 years prior, we obtain results which are very similar to our baseline results (correlation greater than .99).

Third, we assess whether there is some other form of discrimination or mismatch by measuring how the earnings premium for rich country workers *within* an occupation varies according to the skill requirements of the occupation. If our results are driven by one of these barriers to entry, then only the best (or best-matched) poor country workers will make it into occupations which we label as requiring rich country skills. Therefore, poor country workers would look strongest relative to rich-country occupational peers when working in occupations that our main results describe as being intensive in rich country skills. Blair and Chung (2020) provide a formal model of this mechanism.

To investigate whether this is the case, for each occupation j, we regress individual earnings on log of origin country GDP per capita for every worker in that occupation. Call the resulting coefficient estimate $\widehat{\alpha}_j$ for occupation j. Then, for each skill s, we estimate the regression

[15]Using data from November 2019 to March 2021, we code an individual as requiring a license if they report that their job requires active professional certification or license, or has a government-issued professional certification or license, or if they report that certification is required for their job.

Figure 2: Within-occupation coefficient estimates and main results



Note.- Scatterplot of within-occupation coefficient $(\widehat{\theta}^s)$ against main results using income-conditional standard deviations reweighed $(\widehat{\beta}^s)$. Each point represents a skill s.

$$\widehat{\alpha}_j = \psi^s + \theta^s Occ_j^s + \nu_j^s.$$

Figure 2 plots the resulting within-occupation coefficient estimate $\widehat{\theta}^s$ against the main result coefficient $\widehat{\beta}^s$ for each skill s. Two things are notable.

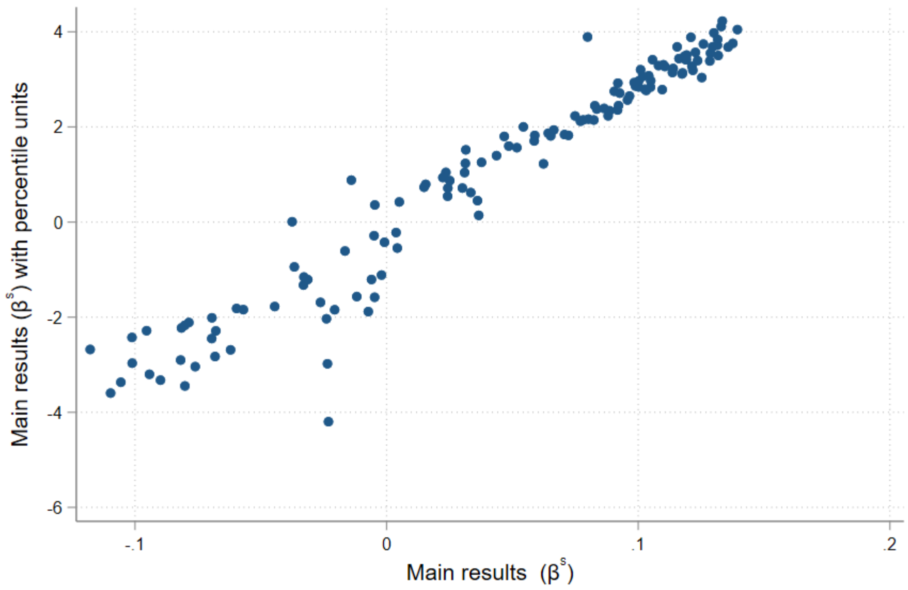
First, skills with larger $\widehat{\theta}^s$ also have larger $\widehat{\beta}^s$. That is, rich countries workers have the greatest within-occupation earnings advantage in occupations which use what our main results imply are rich-country skills. This suggests that our main results are more likely to be understated than overstated.

Second, there is a tight relationship between $\widehat{\theta}^s$ and $\widehat{\beta}^s$. (The correlation is 0.97.) This suggests that, while the use of occupation as an imperfect skill proxy might attenuate the absolute magnitude of our results, it likely does little to change the *relative* magnitudes, i.e. this would not distort the ranking of skills given by our main results.

Arbitrary units Skills do not have well-defined units. The O*NET measures of skill are based on questionnaires which score aspects of job requirements on a 1-7 scale, but there is no reason why the difference between a 1 and a 2 should be considered "the same" as the difference between a 2 and a 3 for any given skill. In this respect, skill measures might be understood as being ordinal as much as cardinal. This can potentially make our results sensitive to an alternative rank-preserving measure of skill. However, in Section 2, we showed that, if there are shifts throughout the distribution of income-conditional skills, our results would not be sensitive to such rank-preserving changes.

We investigate the possible sensitivity of our results in two ways. First, we run our results by measuring income-conditional skills using a percentile within a bin of income (analogous to p_i^A in Section 2), rather than a number of standard deviations above or below the average. Figure

Figure 3: Results under percentile units



Note.- Scatterplot of main results ($\widehat{\beta^s}$) using income-conditional percentile units against baseline version of main results (using income-conditional standard deviations reweighed). Each point represents a skill s.

3 shows the relationship between coefficients estimated in this way and our main results. The correlation is 0.97.

Second, based on the discussion in Section 2, we replace our baseline measure of income-conditional skills with dummies for whether an individual is at least at the 25th, 50th, or 75th percentile of usage of skill s among workers in the same income bin. In general, skills with positive $\widehat{\beta^s}$ have positive coefficients for the probability of being at least at all three of these percentiles. The correlations with our main results for these three percentiles are 0.91, 0.94, and 0.91 for the 25th, 50th, and 75th percentiles, respectively.

These findings suggest that our main results are not likely to be sensitive to alternative ways of measuring skill which preserve the same ordinal ranking.

4.2 Non-random selection of immigrants

Another reason it might be difficult to draw conclusions about the skills of workers within rich and poor countries based on our study of immigrants is that immigrants to the United States are a non-random sample of workers from their origin country.

It is not necessarily a problem if immigrants are unrepresentative, so long as they are equally unrepresentative in rich as in poor countries.[16] However, if immigration is differently non-random with respect to skill levels in rich versus poor countries, it will bias our estimates of skill differences between rich and poor countries.

Two factors lead to non-randomness. The first is that not everyone wishes to move to the US. The second is that, thanks to immigration laws, not everyone who wishes to move is able to. If individuals' skills are correlated with the interest or ability to move to the US, this will lead

[16] Specifically, the condition in which there would be no bias would be if the difference between the average occupational skill usage of immigrants and the skills non-immigrants would have used if they had immigrated were uncorrelated with GDP per capita.

immigrants to be unrepresentative.

A brief description of US immigration laws may help readers understand the second factor. Foreign-born workers who would be present in the US and therefore potentially included in our sample can be in the US either (i) as permanent residents (roughly 13.6 million people as of 2019), (ii) on non-immigrant visas (roughly 2.3 million, of whom roughly half are temporary workers, as opposed to students or diplomats), or (iii) illegally (estimated to be roughly 12 million as of 2015, though many have been in the US longer than five years and therefore would not be in our primary sample).[17] Some of the recently-arrived workers in our data might also be US citizens – for instance, if they obtained permanent residence via marriage to a US citizen and chose to naturalize after three years (other forms of permanent residence require five years of residence before naturalizing), or if they were a US citizen at birth due to the citizenship of their parents. Note that the fractions of immigrants within each of these categories might not equal the effective weight in our main results, since our main results aggregate by country.

There are four primary ways to obtain permanent residence (commonly referred to as a "green card") in the US. The most common, accounting for roughly 70% of new permanent residents in recent years (Department of Homeland Security 2019),[18] is through family ties (generally because a spouse, parent, child, or sibling is a citizen or permanent resident). It is also possible to obtain a green card as a refugee or asylee, which accounts for somewhat over 10% of green cards. A third category is employment-based immigration, which also accounts for slightly over 10% of green cards. Workers who obtain a green card through their job are generally selected to be skilled workers. There is also a green card lottery, which accounts for roughly 5% of green cards. This "diversity lottery" is open to all workers with at least a high school education and/or two years of experience in an occupation requiring at least two years of training, provided that these workers come from a country which has sent fewer than 50,000 immigrants to the United States in the last five years. A formula determines the number of visas made available for each region of the world (e.g. Europe); all eligible applicants from the same region have the same probability of winning. Finally, a small fraction of green cards are accounted for by other miscellaneous categories (e.g. Iraqis and Afghans employed by the US government during wars in those places). Additionally, immigrants may work in the US without having obtained permanent residence, typically by obtaining an H-1B, L-1, O-1, E-1, or TN visa.[19] The largest of these non-immigrant visas, the H-1B, accounts for an influx of roughly 150,000 workers per year over the time period studied, as opposed to in excess of 1 million green cards given per year. Therefore, the number of workers given nonimmigrant visas via the H-1B is similar to the number of workers who obtain a green card on the basis of employment status – and indeed, a large fraction of H-1B holders

[17]See Estimates of the Lawful Permanent Resident Population in the United States: 2015-2019, DHS; Nonimmigrants Residing in the United States: Fiscal Year 2016, DHS; and Estimates of the Unauthorized Immigrant Population Residing in the United States, DHS.

[18]See Table 6 of the DHS 2019 document for specific breakdowns of recent green card approvals, and see prior DHS yearbooks for comparable statistics showing a stable pattern of reasons for granting green cards in other recent years.

[19]The ACS uses a two-month residence rule, i.e. survey respondents must have lived or plan to live for 2 months at their current address to be included in the sample. See more details at https://www.census.gov/content/dam/Census/library/publications/2009/acs/ACSResearch.pdf.

go on to obtain permanent residence. In sum, the most common basis for immigration is a family connection to an existing US citizen or permanent resident, though employment-based immigration accounts for a substantial minority.

We perform two main robustness checks to investigate whether non-randomness of immigration can account for our results.

Evidence from the New Immigrant Survey The New Immigrant Survey collects information on a nationally representative sample of new green card recipients, including their occupation in their origin country. We combine this with separate census data from 14 origin countries to ask whether immigrants' occupations in their origin countries had unusual skill requirements, and to what extent this pattern of selection is correlated with origin country GDP per capita.

Our analysis proceeds in two steps. First, for each skill s, we take the difference between new immigrants' skill usage in their origin country and the average use of that skill in the origin country census. Second, we average these differences within each country and regress them on $zGDP_c$. This gives an estimate of the extent to which selection is correlated with origin country GDP per capita.

We find a substantial negative correlation ($-.81$) between the resulting measure of selection and our main results. That is, immigrants from poor countries are unusually *strong* (relative to their countrymen) in the skills which our main results associate with workers from rich countries. Like the within-occupation analysis, this suggests that our main results correctly describe which skills workers from rich countries specialize in but understate the magnitude of skill differences.

These findings make economic sense. Immigration occurs when both a potential immigrant and the US government wish for that person to immigrate. Immigrants whose skills command high skill prices in the US have the greatest economic incentive to migrate. Furthermore, one of the primary motivations of the United States government is to select immigrants who would be economically productive in the United States (and will therefore e.g. pay more in taxes). Both of these considerations favor immigrants who have skills which are well-compensated in the US economy. Because our main results are closely aligned with that same set of skills, then selection of immigrants in general (regardless of origin country) will favor immigrants with the skills that our main results describe as being rich country workers' skills. Furthermore, because workers in poor origin countries have lower levels of these skills, then a policy which selects for workers with a minimum level of rich country skill will contribute to more selection among workers from poor origin countries than for rich origin countries.

However, this robustness check has three important caveats. First, it is restricted to new green card holders, while the ACS data contains all immigrants, so the immigrant populations are not quite comparable. Second, measurement of skills in origin country census data is noisy due to the small number of occupational categories. The origin country censuses codes occupations using ISCO codes, which we must crosswalk to use with O*NET variables. Unlike in ACS data, these codes are not detailed; we have only one-digit occupation codes. Third, we have data for only a limited number of countries, and a limited number of immigrants in the NIS for each of those countries. Each of these contributes imprecision to the resulting estimates.

Brazilian data We also reproduce our main results using data from the 2010 Brazilian census, which also contains information on detailed occupation, income, and country of birth.[20] The rationale for this robustness check is that immigrants to Brazil are presumably differently selected than immigrants to the United States. We anticipate differences in selection of immigrants because (i) the factors which attract someone to live in Brazil might be different from the factors attracting someone to live in the US, (ii) because immigration laws differ by country (e.g., Brazil allows residents of most other South American countries to immigrate with nearly no restrictions), and (iii) because even superficially similar rules allowing family-based immigration have substantially different impacts in Brazil than in the US due to different historical patterns of immigration.

For a variety of reasons, we consider our US estimates to be more reliable. The primary issue is that the Brazilian data contains very few origin countries with adequate sample to perform our analyses given sample restrictions – for our main results, in which we restrict to using data from countries with at least 20 workers between the ages of 25 and 60 who immigrated within the last 5 years, only 17 countries. As a consequence, the Brazil results are far less precise. Another shortcoming of the Brazilian data is additional measurement error: O*NET's measures of occupational skills were designed to measure skill requirements in the United States, which might not be the same as skill requirements in Brazil, and we must crosswalk occupation codes between the Brazilian data (which codes occupations using the ISCO-08 classification) and O*NET. However, we believe that the Brazilian results are still potentially informative.

The results from Brazil are described in Appendix C. The results are similar to the results in the US, though not identical; the correlation between the coefficient on a particular skill in the US and in Brazil is 0.58 using income-conditional skills with reweighting. However, small sample sizes in Brazil add noise to our estimates which may substantially attenuate this correlation; for example, the correlation between US and Brazilian results *without* educational reweighting is 0.77. (Reweighting reduces effective sample size – essentially, a reduction in bias at a cost in variance.) Furthermore, the primary takeaways from the US data are also present in the Brazilian data.

5 Discussion

The primary goal of our paper is simply to document differences in skills. However, our results also have implications for why some countries are better at producing human capital than others. In this section, we engage in a more speculative discussion of what our results suggest about why rich countries produce more human capital than poor countries.

[20]We use data from IPUMS USA: Version 10.0 [dataset]. Minneapolis: IPUMS, 2020. https://doi.org/10.18128/D010.V10.0

Among the various ways to characterize our results discussed in Section 3, the one which most precisely characterized our results was that the skills of rich country workers are the same as the skills which differentiate high-earning Americans from low-earning Americans. That is, rich country workers specialize in the set of skills which are well-compensated in the American economy. Furthermore, because the correlation is so strong (0.95 for reweighted unconditional skills, and 0.91 for reweighted income-conditional skills), the fact that rich country workers are stronger in exactly those skills which are well-compensated in the American economy nearly entirely describes the relevant dimensions of skill difference.

A natural explanation for this correlation is that the greater accumulation of these skills in rich countries is a *consequence* of the fact that these skills are well-compensated.

It is obvious that the usefulness of skills is context-dependent, and that people respond by accumulating the sort of skills needed for their situation. Hunter-gatherers learn how to find food in the wilderness but may not learn basic arithmetic, while the opposite is true for New Yorkers, because those are the skills which are practical in their context.

What is less obvious is the extent to which this accounts for skill differences across countries, as opposed to idiosyncratic factors such as the competence of school leaders or cultural quirks which arise for non-economic reasons.

A simple way to conceptualize these explanations is with country-specific supply and demand curves for each skill. One explanation above is that skill quantity differences across countries are due to differences in skill demand curves. The other is based on differences in skill supply curves.

Our main results are most consistent with explanations based on skill demand. Shifts in the demand curve simultaneously increase both prices and quantities, while shifts in supply generate decreases in price as quantity increases. Our main estimates find that, across a large range of skills, advanced economies provide greater quantities of the skills which are highly rewarded in an advanced economy – i.e., high quantities coincide with high prices.

We can also use the NIS data to show that the prices of rich country skills are not just high in the US (a rich country economy), but in fact higher in the US than elsewhere, as is required for this explanation. To do this, we ask who has a greater earnings gain at migration: workers with rich country skills, or workers who have the same origin country earnings in an origin country with the same GDP per capita but with skills less typical of rich country workers. Econometrically, we construct the earnings gain at migration as the difference between the log of an immigrant's earnings in the US and their log earnings in their origin country. Then, for each skill s, we regress individuals' earnings gain at migration on their usage of skill s in their last occupation in their origin country, while controlling for home country log earnings, home country GDP per capita, and the interaction of home country log earnings with home country GDP per capita.[21] The resulting coefficients for each skill s have a correlation of 0.58 with our main results despite substantial sampling error due to the fact that we have fewer than 1000 observations with all the

[21] That is, we run a separate such regression for each skill s. Observations in these regressions are individuals. Results are not sensitive to using earnings without taking a log.

required variables. That is, the skills which result in larger earnings gains when immigrating to the US are quite similar to the skills which rich country workers have more of.

Note that neither the demand-based nor supply-based explanation conflicts with explanations of human capital differences such as those cited in the introduction which emphasize specific inputs such as schooling, culture, or learning on the job. To the extent that these inputs explain cross-country skill differences, the demand-based explanation would take the view that these inputs are the mechanism by which quantity rises in response to price increases, while the supply-based explanation would view these inputs as differing across countries for other reasons. The chief distinction with respect to levels of these inputs is that the demand-based explanation implies that inputs which produce similar skills should be positively correlated across countries, while supply-based explanations would not necessarily imply such a correlation.

We next consider two other ways of evaluating the plausibility of the demand-based explanation using skills data.

Relationship with technological differences If the demand-based explanation is correct, then specific differences in skills should be traceable to specific differences in technology. Relative to poor countries, rich countries produce more complex goods (Hidalgo and Hausmann 2009) in larger firms (e.g., Tybout 2000, Poschke 2018) which are closer to the technological frontier (Jones and Romer 2010, Poschke 2018) and invest more in R&D (Arkolakis et al. 2018). We argue that each of these features makes the forms of human capital from Section 3 particularly practical.

Managerial skill is presumably more important in contexts where there are people to manage. Larger firms require the coordination of the efforts of many people. More complex production processes, involving more people playing more specialized roles, require managerial skill to coordinate the efforts of people doing more distinct tasks. Some empirical support for the importance of managerial skill in rich country technologies comes from Bahar et al. (2019), who study technological transfer from Germany to Yugoslavia and document that this technological transfer led to the greatest productivity improvements when the technology used managerial skills.

Demand for ideas-related skills is also likely to be higher in rich country economies. Ideas are less valuable in very small businesses, because the fixed cost of coming up with an idea is divided by relatively few units of production (Schumpeter 1942); the same percent increase in productivity might be worth thousands of dollars in a small firm but worth millions in a large firm. Though the literature is unclear about whether medium or large firms are more innovative (e.g., Symeonidis 1996), the smallest firms rarely devote any resources to R&D, and there is evidence that features of the economic environment which increase the optimal scale of firms also lead to increases in innovation (Pagano and Schivardi 2003). To the extent that the margin between small and medium-sized firms is important for innovative activity, that aspect of the firm size distribution is indeed very different between rich and poor countries; for example, in Ethiopia manufacturing micro-enterprises account for 97 percent of employment while in the United States micro-enterprises account for 26 percent of private sector employment (Li and Rama 2015).

Beyond firm size, firms in advanced economies are more likely to be at the technological frontier, and therefore are more likely to need to innovate to gain a technological advantage, rather than simply imitating existing technologies (Jones and Romer 2010). This would also raise the value of idea-generating skills. The fact that rich country firms spend more on R&D (Arkolakis et al. 2018) also suggests that there might be higher demand for idea-generating skills in rich countries – though of course these expenditures might be endogenous to the supply of labor with idea-generating skills.

Specialization To further explore the hypothesis that rich country skills are well-adapted to rich country technologies, we generate a prediction based on this view and test it.

Our prediction is that workers from rich countries should have more specialized skills than workers from poor countries. The sort of complex production processes which are more prevalent in rich countries involve a greater degree of specialization of workers into roles. Hidalgo and Hausmann (2009) argue that advanced economies are able to effectively possess more knowledge about the world by assigning different knowledge and skills to different people – e.g., for consumers to be able to purchase toothpaste, it suffices that *someone* knows how to make it, so it is just as well that only a few people know how to make toothpaste while other people focus on knowing other things.

Therefore, if rich country workers have human capital matching the technological demands of advanced economies, we would expect rich country workers to have more specialized human capital, in the sense they should be more (i) varied and (ii) narrow in their strengths.

Our first test is whether the within-country variance of income-conditional skills is higher for rich countries. This within-country variance is constructed as

$$var_c := \frac{1}{S} \sum_s \left[\frac{1}{N_c - 1} \sum_{i \in C} \left(Z_i^s - \frac{1}{N_c} \sum_{j \in C} Z_j^s \right)^2 \right],$$

where Z_i^s is individual i's income-conditional (standardized) skill s, C is the set of individuals from country c, N_c is the number of individuals from country c, and S is the total number of skills. That is, we construct the sample variance of income-conditional skill for each skill, then take the average of this variance across all skills.[22]

Finally, we regress var_c on log of GDP per capita. The results are shown in the top panel of Table 4.

Our second test is to ask whether workers from rich countries work in more lopsided occupations, i.e. occupations where workers specialize narrowly in being great at only a few things rather than being good at many things. As an example, professional basketball players are quite unusual relative to most high-earning workers, both because their occupation has an unusually high

[22] We eliminate observations with only a single observation from a country in a given survey year, since the sample variance would otherwise be 0.

Table 4: Regression of variance on log of GDP per capita

Variance results	
Log of GDP per capita in origin country	0.075 (0.009)
Observations	1,817
Lopsidedness results	
Log of GDP per capita in origin country	0.039 (0.008)
Observations	1,826

Standard errors in parentheses clustered at the country level.

requirement for physical skills and because their occupation has an unusually low requirement for cognitive skills.

We operationalize this notion of "lopsided" as follows. First, we divide occupations into deciles of average income. Next, among occupations within each decile, we calculate how many standard deviations above or below the average each occupation j is for each skill s. Lastly, we compute the extent of lopsidedness in occupation j, denoted as L_j, as the sum of the squares of these deviations across all skills. This credits an occupation as having unusual skill requirements if either its skill requirements are unusually high or unusually low.

We then take averages of L_j among workers from each country in each year of the ACS, and use this as an outcome variable in regressions which are otherwise identical to those used in producing our main results. The results are shown in the bottom panel of Table 4.

Both sets of results suggest that workers from high-income countries develop more varied forms of human capital, rather than all accumulating the same skills. Workers sorting into occupations which provide them a comparative advantage can in principle lead to higher apparent human capital in rich countries.

However, it is difficult to interpret magnitudes in the above results, so they should properly be considered only to be suggestive. While the results support the view that workers in rich countries engage in a greater degree of specialization of human capital, we cannot say from these results whether this mechanism is quantitatively important in explaining the higher apparent human capital of workers from rich countries. Instead, we interpret it merely in the spirit of testing a prediction of the demand-based explanation; had there not been differences in the extent of specialization, this would have been inconsistent with the demand-based explanation.

6 Conclusion

We measure skill differences between workers from rich and poor countries. We find that there are few differences except that workers from rich countries are better at the skills which are well-compensated in the US economy. This means specifically that rich country workers have the greatest advantage in cognitive skills, and in particular in those cognitive skills related to generating new ideas rather than knowledge of existing ideas or facts. Furthermore, these skills closely match the skills used in managerial occupations. We argue that our results point to differences in demand for skills as an important explanation for cross-country differences in skills.

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Appendix

A Skill indices

The following is a list of O*NET measures used in each skill index.

1. **Creativity:** Fluency of Ideas, Innovation, Operations Analysis, Originality
2. **Critical Thinking:** Active Learning, Analytical Thinking, Category Flexibility, Complex Problem Solving, Critical Thinking, Deductive Reasoning, Inductive Reasoning, Judgment and Decision Making, Monitoring, Systems Analysis, Systems Evaluation
3. **Effort:** Achievement/Effort, Attention to Detail, Dependability, Initiative, Persistence, Self Control, Stress Tolerance, Time Management
4. **Language:** Active Listening, English Language, Foreign Language, Oral Comprehension, Oral Expression, Reading Comprehension, Speaking, Speech Clarity, Speech Recognition, Writing, Written Comprehension, Written Expression
5. **Math:** Mathematical Reasoning, Mathematics, Number Facility
6. **Social:** Concern for Others, Cooperation, Customer and Personal Service, Leadership, Management of Personnel Resources, Negotiation, Persuasion, Service Orientation, Social Orientation, Social Perceptiveness
7. **Technology:** Building and Construction, Computers and Electronics, Equipment Maintenance, Equipment Selection, Food Production, Installation, Mechanical, Operation Monitoring, Operation and Control, Programming, Quality Control Analysis, Repairing, Telecommunications, Troubleshooting
8. **Scientific Knowledge:** Biology, Chemistry, Engineering and Technology, Geography, Medicine and Dentistry, Physics, Psychology, Science
9. **Other Knowledge:** Administration and Management, Clerical, Communications and Media, Economics and Accounting, Education and Training, Fine Arts, History and Archeology, Law and Government, Personnel and Human Resources, Philosophy and Theology, Public Safety and Security, Sales and Marketing, Sociology and Anthropology, Therapy and Counseling, Transportation
10. **Other Cognitive:** Auditory Attention, Flexibility of Closure, Information Ordering, Memorization, Perceptual Speed, Reaction Time, Response Orientation, Selective Attention, Spatial Orientation, Speed of Closure, Time Sharing, Visualization
11. **Physical:** Arm-Hand Steadiness, Control Precision, Depth Perception, Dynamic Flexibility, Dynamic Strength, Explosive Strength, Extent Flexibility, Far Vision, Finger Dexterity,

Glare Sensitivity, Gross Body Coordination, Gross Body Equilibrium, Manual Dexterity, Multilimb Coordination, Near Vision, Night Vision, Peripheral Vision, Rate Control, Sound Localization, Speed of Limb Movement, Stamina, Static Strength, Trunk Strength, Visual Color Discrimination, Wrist-Finger Speed

Full definitions and survey items used to elicit occupational ratings can be found on the O*NET website (onetonline.org). We judge the following skills to be either too ambiguous or too unrelated to the above categories to use in any index: Adaptability/Flexibility, Coordination, Design, Hearing Sensitivity, Independence, Instructing, Integrity, Learning Strategies, Management of Financial Resources, Management of Material Resources, Problem Sensitivity, Production and Processing, Technology Design.

B Main results

Table 5: Complete main results

O*NET		Unconditional		Income Conditional	
Category	Skill	Baseline	Reweighted	Baseline	Reweighted
Knowledge	English Language	0.220	0.212	0.147	0.139
		(0.019)	(0.024)	(0.016)	(0.02)
Skills	Speaking	0.222	0.211	0.144	0.138
		(0.02)	(0.025)	(0.016)	(0.021)
Abilities	Speech Clarity	0.213	0.204	0.139	0.136
		(0.02)	(0.025)	(0.016)	(0.021)
Skills	Management of Personnel Resources	0.213	0.203	0.125	0.133
		(0.017)	(0.019)	(0.011)	(0.014)
Knowledge	Administration and Management	0.205	0.186	0.140	0.133
		(0.016)	(0.018)	(0.013)	(0.014)
Skills	Reading Comprehension	0.250	0.226	0.149	0.132
		(0.021)	(0.024)	(0.016)	(0.019)
Skills	Active Learning	0.246	0.219	0.153	0.132
		(0.020)	(0.024)	(0.015)	(0.019)
Abilities	Originality	0.250	0.219	0.150	0.131
		(0.019)	(0.022)	(0.013)	(0.017)
Abilities	Speech Recognition	0.188	0.198	0.110	0.130
		(0.019)	(0.025)	(0.015)	(0.021)
Skills	Critical Thinking	0.256	0.226	0.148	0.130
		(0.022)	(0.024)	(0.016)	(0.019)
Knowledge	Clerical	0.125	0.170	0.086	0.129
		(0.015)	(0.020)	(0.013)	(0.017)

Abilities	Fluency of Ideas	0.249	0.219	0.146	0.128
		(0.019)	(0.022)	(0.013)	(0.017)
Skills	Complex Problem Solving	0.254	0.223	0.145	0.126
		(0.021)	(0.022)	(0.014)	(0.017)
Abilities	Written Comprehension	0.241	0.222	0.140	0.125
		(0.021)	(0.025)	(0.016)	(0.020)
WorkStyle	Leadership	0.183	0.179	0.117	0.124
		(0.017)	(0.021)	(0.013)	(0.017)
Skills	Persuasion	0.189	0.196	0.103	0.123
		(0.019)	(0.023)	(0.014)	(0.019)
Skills	Active Listening	0.215	0.206	0.126	0.122
		(0.021)	(0.026)	(0.017)	(0.021)
WorkStyle	Persistence	0.225	0.210	0.129	0.121
		(0.020)	(0.023)	(0.015)	(0.019)
Knowledge	Economics and Accounting	0.184	0.160	0.131	0.121
		(0.016)	(0.016)	(0.014)	(0.014)
Skills	Negotiation	0.183	0.189	0.098	0.119
		(0.019)	(0.024)	(0.014)	(0.020)
Skills	Time Management	0.203	0.195	0.114	0.119
		(0.018)	(0.023)	(0.013)	(0.017)
WorkStyle	Initiative	0.229	0.203	0.137	0.119
		(0.020)	(0.024)	(0.015)	(0.020)
Skills	Systems Evaluation	0.251	0.212	0.140	0.118
		(0.021)	(0.021)	(0.014)	(0.016)
Abilities	Written Expression	0.230	0.209	0.135	0.118
		(0.022)	(0.026)	(0.017)	(0.021)
Abilities	Oral Comprehension	0.199	0.201	0.112	0.117
		(0.021)	(0.026)	(0.017)	(0.022)
Skills	Systems Analysis	0.254	0.211	0.141	0.116
		(0.021)	(0.021)	(0.014)	(0.016)
Abilities	Memorization	0.190	0.191	0.112	0.115
		(0.019)	(0.022)	(0.016)	(0.019)
Abilities	Oral Expression	0.199	0.188	0.126	0.114
		(0.021)	(0.026)	(0.017)	(0.022)
Knowledge	Mathematics	0.191	0.185	0.112	0.114
		(0.016)	(0.016)	(0.013)	(0.015)
Knowledge	Personnel and Human Resources	0.166	0.150	0.118	0.111
		(0.014)	(0.016)	(0.012)	(0.014)
Knowledge	Communications and Media	0.196	0.173	0.124	0.110

		(0.019)	(0.023)	(0.015)	(0.019)
Skills	Writing	0.230	0.201	0.134	0.110
		(0.022)	(0.026)	(0.017)	(0.021)
Skills	Operations Analysis	0.231	0.196	0.122	0.108
		(0.016)	(0.015)	(0.010)	(0.010)
Knowledge	Geography	0.171	0.144	0.124	0.106
		(0.014)	(0.015)	(0.011)	(0.012)
Skills	Judgment and Decision Making	0.230	0.201	0.119	0.105
		(0.020)	(0.023)	(0.014)	(0.018)
Abilities	Category Flexibility	0.224	0.191	0.126	0.105
		(0.018)	(0.018)	(0.012)	(0.014)
Knowledge	Computers and Electronics	0.196	0.184	0.094	0.104
		(0.017)	(0.017)	(0.013)	(0.014)
Abilities	Deductive Reasoning	0.241	0.204	0.129	0.103
		(0.021)	(0.023)	(0.015)	(0.018)
Abilities	Mathematical Reasoning	0.212	0.191	0.110	0.103
		(0.019)	(0.020)	(0.015)	(0.017)
Knowledge	Sales and Marketing	0.111	0.122	0.082	0.102
		(0.013)	(0.016)	(0.013)	(0.016)
WorkStyle	Achievement/Effort	0.226	0.181	0.142	0.101
		(0.019)	(0.021)	(0.014)	(0.017)
Skills	Coordination	0.167	0.163	0.087	0.100
		(0.016)	(0.021)	(0.012)	(0.017)
Knowledge	Law and Government	0.172	0.15	0.113	0.100
		(0.018)	(0.018)	(0.014)	(0.015)
Abilities	Speed of Closure	0.184	0.184	0.087	0.099
		(0.018)	(0.021)	(0.013)	(0.016)
Skills	Learning Strategies	0.202	0.169	0.128	0.098
		(0.019)	(0.024)	(0.015)	(0.020)
Abilities	Information Ordering	0.216	0.191	0.101	0.097
		(0.018)	(0.019)	(0.012)	(0.015)
Skills	Management of Financial Resources	0.172	0.167	0.077	0.096
		(0.016)	(0.017)	(0.010)	(0.014)
Abilities	Number Facility	0.193	0.174	0.101	0.093
		(0.018)	(0.020)	(0.015)	(0.018)
WorkStyle	Analytical Thinking	0.224	0.19	0.115	0.092
		(0.020)	(0.020)	(0.015)	(0.016)
Skills	Technology Design	0.172	0.163	0.078	0.092
		(0.015)	(0.015)	(0.010)	(0.012)

Skills	Monitoring	0.179	0.161	0.097	0.092
		(0.018)	(0.023)	(0.014)	(0.019)
Skills	Instructing	0.178	0.151	0.114	0.090
		(0.018)	(0.023)	(0.015)	(0.020)
Abilities	Inductive Reasoning	0.227	0.187	0.115	0.089
		(0.021)	(0.022)	(0.016)	(0.018)
Abilities	Selective Attention	0.101	0.141	0.045	0.088
		(0.010)	(0.014)	(0.009)	(0.012)
Skills	Mathematics	0.194	0.170	0.098	0.086
		(0.018)	(0.020)	(0.014)	(0.018)
Abilities	Flexibility of Closure	0.170	0.170	0.074	0.084
		(0.015)	(0.017)	(0.010)	(0.012)
Knowledge	Education and Training	0.134	0.115	0.102	0.083
		(0.014)	(0.016)	(0.012)	(0.014)
WorkStyle	Innovation	0.197	0.159	0.109	0.082
		(0.016)	(0.019)	(0.012)	(0.015)
WorkStyle	Integrity	0.146	0.144	0.079	0.080
		(0.019)	(0.024)	(0.016)	(0.021)
Skills	Programming	0.158	0.134	0.078	0.080
		(0.015)	(0.012)	(0.011)	(0.010)
WorkStyle	Adaptability/Flexibility	0.134	0.141	0.066	0.078
		(0.018)	(0.024)	(0.016)	(0.022)
Skills	Management of Material Resources	0.146	0.142	0.063	0.077
		(0.013)	(0.015)	(0.008)	(0.012)
Abilities	Time Sharing	0.037	0.096	0.020	0.075
		(0.010)	(0.015)	(0.010)	(0.014)
Knowledge	History and Archeology	0.127	0.078	0.121	0.072
		(0.013)	(0.015)	(0.013)	(0.015)
Abilities	Near Vision	0.155	0.154	0.063	0.071
		(0.014)	(0.016)	(0.010)	(0.013)
Knowledge	Design	0.132	0.117	0.070	0.066
		(0.011)	(0.013)	(0.010)	(0.014)
Knowledge	Engineering and Technology	0.152	0.127	0.075	0.065
		(0.012)	(0.011)	(0.009)	(0.013)
WorkStyle	Dependability	0.090	0.110	0.042	0.064
		(0.015)	(0.023)	(0.014)	(0.020)
Knowledge	Building and Construction	0.041	0.058	0.048	0.062
		(0.011)	(0.018)	(0.011)	(0.018)
WorkStyle	Attention to Detail	0.137	0.138	0.049	0.059

		(0.014)	(0.017)	(0.011)	(0.015)
Abilities	Problem Sensitivity	0.170	0.157	0.059	0.059
		(0.020)	(0.024)	(0.015)	(0.020)
Skills	Social Perceptiveness	0.116	0.109	0.051	0.054
		(0.019)	(0.027)	(0.017)	(0.025)
WorkStyle	Cooperation	0.063	0.092	0.022	0.052
		(0.016)	(0.024)	(0.015)	(0.021)
Knowledge	Telecommunications	0.093	0.115	0.007	0.049
		(0.014)	(0.018)	(0.012)	(0.016)
Skills	Science	0.157	0.112	0.079	0.047
		(0.015)	(0.014)	(0.012)	(0.013)
WorkStyle	Stress Tolerance	0.061	0.083	0.016	0.044
		(0.016)	(0.024)	(0.015)	(0.022)
Abilities	Visualization	0.079	0.080	0.032	0.038
		(0.010)	(0.014)	(0.010)	(0.015)
Knowledge	Fine Arts	0.046	0.040	0.041	0.037
		(0.008)	(0.012)	(0.008)	(0.012)
Knowledge	Physics	0.093	0.075	0.052	0.036
		(0.009)	(0.010)	(0.009)	(0.012)
Abilities	Perceptual Speed	0.055	0.095	-0.011	0.033
		(0.010)	(0.013)	(0.009)	(0.013)
Knowledge	Psychology	0.061	0.060	0.028	0.031
		(0.017)	(0.022)	(0.017)	(0.021)
Knowledge	Production and Processing	0.019	0.018	0.035	0.031
		(0.015)	(0.020)	(0.015)	(0.020)
Knowledge	Sociology and Anthropology	0.089	0.060	0.053	0.031
		(0.018)	(0.022)	(0.017)	(0.020)
Knowledge	Customer and Personal Service	-0.005	0.032	-0.005	0.03
		(0.012)	(0.019)	(0.012)	(0.019)
Knowledge	Biology	0.066	0.036	0.053	0.025
		(0.010)	(0.010)	(0.009)	(0.010)
Skills	Installation	0.000	0.038	-0.009	0.024
		(0.009)	(0.015)	(0.009)	(0.014)
WorkStyle	Independence	0.084	0.059	0.048	0.024
		(0.013)	(0.016)	(0.011)	(0.015)
Abilities	Far Vision	-0.004	0.022	0.005	0.024
		(0.010)	(0.014)	(0.010)	(0.014)
Skills	Service Orientation	0.026	0.049	-0.001	0.022
		(0.017)	(0.026)	(0.016)	(0.024)

Knowledge	Philosophy and Theology	0.039	0.023	0.033	0.016
		(0.014)	(0.018)	(0.014)	(0.018)
WorkStyle	Social Orientation	-0.036	-0.005	-0.011	0.015
		(0.014)	(0.019)	(0.015)	(0.021)
WorkStyle	Self Control	-0.029	-0.001	-0.020	0.005
		(0.014)	(0.018)	(0.014)	(0.018)
Knowledge	Mechanical	-0.034	-0.015	-0.006	0.004
		(0.014)	(0.019)	(0.013)	(0.018)
Knowledge	Foreign Language	-0.036	-0.025	0.000	0.004
		(0.009)	(0.011)	(0.008)	(0.011)
Knowledge	Transportation	-0.061	-0.035	-0.014	-0.001
		(0.012)	(0.014)	(0.011)	(0.015)
Abilities	Peripheral Vision	-0.094	-0.053	-0.038	-0.002
		(0.013)	(0.019)	(0.012)	(0.018)
WorkStyle	Concern for Others	-0.048	-0.024	-0.020	-0.005
		(0.015)	(0.019)	(0.015)	(0.021)
Abilities	Night Vision	-0.092	-0.051	-0.039	-0.005
		(0.014)	(0.02)	(0.012)	(0.018)
Abilities	Auditory Attention	-0.091	-0.034	-0.049	-0.005
		(0.011)	(0.013)	(0.009)	(0.012)
Abilities	Sound Localization	-0.098	-0.057	-0.040	-0.006
		(0.013)	(0.019)	(0.011)	(0.018)
Abilities	Glare Sensitivity	-0.093	-0.059	-0.035	-0.007
		(0.014)	(0.020)	(0.013)	(0.019)
Abilities	Spatial Orientation	-0.101	-0.065	-0.041	-0.012
		(0.014)	(0.018)	(0.012)	(0.017)
Knowledge	Therapy and Counseling	-0.012	-0.005	-0.020	-0.014
		(0.017)	(0.020)	(0.017)	(0.022)
Knowledge	Public Safety and Security	-0.086	-0.045	-0.044	-0.017
		(0.013)	(0.015)	(0.013)	(0.016)
Skills	Repairing	-0.079	-0.055	-0.036	-0.021
		(0.014)	(0.020)	(0.012)	(0.018)
Abilities	Dynamic Flexibility	-0.119	-0.102	-0.039	-0.023
		(0.017)	(0.022)	(0.013)	(0.019)
Skills	Equipment Maintenance	-0.083	-0.062	-0.037	-0.024
		(0.014)	(0.020)	(0.012)	(0.018)
Skills	Equipment Selection	-0.051	-0.043	-0.028	-0.024
		(0.014)	(0.020)	(0.013)	(0.019)
Knowledge	Food Production	-0.095	-0.092	-0.026	-0.026

		(0.011)	(0.014)	(0.009)	(0.012)
Abilities	Visual Color Discrimination	-0.071	-0.047	-0.046	-0.031
		(0.013)	(0.017)	(0.012)	(0.016)
Knowledge	Chemistry	-0.005	-0.033	0.003	-0.033
		(0.009)	(0.012)	(0.009)	(0.012)
Abilities	Hearing Sensitivity	-0.105	-0.058	-0.068	-0.033
		(0.011)	(0.014)	(0.009)	(0.013)
Skills	Quality Control Analysis	-0.036	-0.020	-0.051	-0.037
		(0.013)	(0.016)	(0.013)	(0.017)
Knowledge	Medicine and Dentistry	-0.031	-0.026	-0.042	-0.038
		(0.014)	(0.016)	(0.016)	(0.019)
Skills	Operation Monitoring	-0.077	-0.056	-0.062	-0.044
		(0.013)	(0.018)	(0.012)	(0.018)
Abilities	Depth Perception	-0.132	-0.104	-0.079	-0.057
		(0.015)	(0.019)	(0.013)	(0.017)
Skills	Operation and Control	-0.136	-0.109	-0.079	-0.060
		(0.016)	(0.021)	(0.013)	(0.018)
Abilities	Rate Control	-0.160	-0.135	-0.079	-0.062
		(0.018)	(0.024)	(0.015)	(0.02)
Abilities	Control Precision	-0.166	-0.13	-0.096	-0.068
		(0.019)	(0.023)	(0.015)	(0.020)
Abilities	Gross Body Equilibrium	-0.190	-0.147	-0.097	-0.068
		(0.018)	(0.020)	(0.014)	(0.016)
Abilities	Wrist-Finger Speed	-0.148	-0.132	-0.075	-0.069
		(0.018)	(0.023)	(0.014)	(0.020)
Skills	Troubleshooting	-0.104	-0.081	-0.085	-0.069
		(0.014)	(0.017)	(0.013)	(0.017)
Abilities	Reaction Time	-0.180	-0.143	-0.101	-0.076
		(0.017)	(0.02)	(0.013)	(0.016)
Abilities	Multilimb Coordination	-0.198	-0.161	-0.100	-0.079
		(0.020)	(0.022)	(0.015)	(0.018)
Abilities	Explosive Strength	-0.171	-0.136	-0.104	-0.080
		(0.016)	(0.016)	(0.014)	(0.016)
Abilities	Finger Dexterity	-0.173	-0.131	-0.108	-0.080
		(0.018)	(0.021)	(0.014)	(0.018)
Abilities	Dynamic Strength	-0.206	-0.173	-0.105	-0.082
		(0.020)	(0.022)	(0.015)	(0.018)
Abilities	Response Orientation	-0.179	-0.145	-0.105	-0.082
		(0.016)	(0.019)	(0.013)	(0.016)

Abilities	Speed of Limb Movement	-0.204	-0.174	-0.107	-0.090
		(0.019)	(0.021)	(0.015)	(0.017)
Abilities	Gross Body Coordination	-0.214	-0.181	-0.114	-0.094
		(0.019)	(0.021)	(0.014)	(0.017)
Abilities	Arm-Hand Steadiness	-0.206	-0.167	-0.120	-0.095
		(0.020)	(0.023)	(0.016)	(0.019)
Abilities	Extent Flexibility	-0.217	-0.19	-0.116	-0.101
		(0.020)	(0.023)	(0.015)	(0.018)
Abilities	Manual Dexterity	-0.209	-0.178	-0.121	-0.101
		(0.021)	(0.024)	(0.016)	(0.020)
Abilities	Stamina	-0.222	-0.193	-0.120	-0.106
		(0.020)	(0.021)	(0.015)	(0.017)
Abilities	Static Strength	-0.226	-0.196	-0.125	-0.110
		(0.020)	(0.021)	(0.015)	(0.017)
Abilities	Trunk Strength	-0.227	-0.208	-0.120	-0.118
		(0.020)	(0.021)	(0.014)	(0.016)

Note.- List of all coefficients in regressions of skill usage (in standard deviations) on log of GDP per capita (in standard deviations), controlling for survey year fixed effects. Columns (1) and (2) present the results using unconditional skills, while columns (3) and (4) present the income-conditional skills indices. Columns (2) and (4) are the results weighted using the Barro- Lee weights. For the skill indices definition, see Appendix A. Baseline: $N = 2,212$; Weighted: $N = 1,826$. Robust standard errors clustered at the country level in parentheses.

C Results from Brazilian data

As a robustness check described in Section 4, we also run our main results using the 2010 long form Brazilian census. The specification is lightly modified from our ACS specification because we are working with only a single wave of data (prior years of the Brazilian census used only two-digit occupation codes, which is not detailed enough to reliably match to O*NET measures).

We only include individuals who are employed, since these are the ones with occupation information and income. For this subsample we have the birthplace and occupation information.

As in our main results, for each country of birth, we construct the average income-conditional skill, measured in units of standard deviations above or below the average within the same income decile (i.e., a separate mean and standard deviation of each skill is calculated for each income decile to produce this measure).

Our regressions use individuals who immigrated within the five years before the census. Moreover, we want to concentrate on people of working age, so we estimate only including those with age between 25 and 60. We aggregate observations to the country level by averaging, and only use countries which have at least 20 people on the dataset. In the Brazilian data, this results in a sample consisting of only 17 countries.

Results for our main analysis, performed on Brazilian data, are shown in Table 6. Note that these results are considerably more noisy than the estimates from US data; e.g., most coefficient estimates are not statistically significant, in contrast with the US estimates where the great majority of coefficients are statistically significant.

Table 6: Brazil data robustness check

		Main results	
O*NET category	Skill	Coef.	Std.Err.
Knowledge	Food Production	0.282	(0.148)
Knowledge	Education and Training	0.260	(0.096)
Abilities	Memorization	0.257	(0.066)
WorkStyle	Innovation	0.253	(0.051)
Knowledge	History and Archeology	0.237	(0.104)
Knowledge	Fine Arts	0.233	(0.089)
Abilities	Time Sharing	0.228	(0.099)
Skills	Instructing	0.224	(0.080)
WorkStyle	Adaptability/Flexibility	0.221	(0.067)
Abilities	Auditory Attention	0.213	(0.079)
WorkStyle	Dependability	0.207	(0.072)
WorkStyle	Cooperation	0.205	(0.075)
WorkStyle	Stress Tolerance	0.205	(0.067)
Abilities	Speed of Closure	0.201	(0.086)
Skills	Learning Strategies	0.201	(0.077)
Knowledge	English Language	0.200	(0.085)
WorkStyle	Persistence	0.197	(0.094)
WorkStyle	Leadership	0.194	(0.101)
Abilities	Originality	0.183	(0.072)
Knowledge	Foreign Language	0.173	(0.099)
Knowledge	Geography	0.171	(0.076)
Skills	Technology Design	0.170	(0.105)
WorkStyle	Social Orientation	0.168	(0.081)
Abilities	Fluency of Ideas	0.166	(0.067)
WorkStyle	Initiative	0.163	(0.110)
Skills	Systems Evaluation	0.162	(0.077)
WorkStyle	Self Control	0.158	(0.078)
Skills	Mathematics	0.157	(0.074)
Skills	Active Learning	0.154	(0.081)
Skills	Management of Personnel Resources	0.153	(0.100)
Abilities	Number Facility	0.152	(0.067)

Knowledge	Philosophy and Theology	0.151	(0.084)
Skills	Systems Analysis	0.148	(0.073)
Abilities	Hearing Sensitivity	0.147	(0.085)
Abilities	Selective Attention	0.146	(0.056)
Knowledge	Sociology and Anthropology	0.146	(0.100)
Knowledge	Psychology	0.140	(0.087)
WorkStyle	Analytical Thinking	0.139	(0.088)
Knowledge	Therapy and Counseling	0.139	(0.066)
Abilities	Mathematical Reasoning	0.139	(0.071)
Abilities	Problem Sensitivity	0.136	(0.098)
WorkStyle	Achievement/Effort	0.134	(0.095)
Skills	Time Management	0.133	(0.096)
Knowledge	Mathematics	0.132	(0.108)
Skills	Monitoring	0.126	(0.081)
Knowledge	Communications and Media	0.125	(0.090)
Knowledge	Design	0.122	(0.098)
Abilities	Oral Expression	0.119	(0.092)
Abilities	Deductive Reasoning	0.118	(0.084)
WorkStyle	Concern for Others	0.115	(0.082)
Abilities	Written Comprehension	0.109	(0.087)
Knowledge	Personnel and Human Resources	0.109	(0.134)
Skills	Critical Thinking	0.108	(0.095)
Skills	Coordination	0.106	(0.129)
Abilities	Category Flexibility	0.105	(0.095)
Knowledge	Chemistry	0.099	(0.096)
Skills	Negotiation	0.098	(0.115)
Abilities	Speech Clarity	0.098	(0.109)
Skills	Installation	0.098	(0.103)
Knowledge	Engineering and Technology	0.096	(0.104)
Knowledge	Public Safety and Security	0.091	(0.125)
Abilities	Written Expression	0.091	(0.108)
Abilities	Oral Comprehension	0.089	(0.108)
Skills	Speaking	0.088	(0.115)
Knowledge	Law and Government	0.088	(0.108)
Skills	Service Orientation	0.088	(0.129)
Knowledge	Physics	0.085	(0.088)
Knowledge	Computers and Electronics	0.084	(0.096)
Skills	Social Perceptiveness	0.084	(0.117)
Abilities	Inductive Reasoning	0.083	(0.084)

Skills	Reading Comprehension	0.079	(0.091)
Skills	Writing	0.075	(0.086)
Skills	Judgment and Decision Making	0.072	(0.072)
WorkStyle	Independence	0.070	(0.085)
WorkStyle	Integrity	0.067	(0.072)
Abilities	Trunk Strength	0.066	(0.099)
Skills	Programming	0.066	(0.086)
Skills	Management of Material Resources	0.066	(0.143)
Knowledge	Production and Processing	0.065	(0.127)
Knowledge	Administration and Management	0.064	(0.128)
Skills	Persuasion	0.062	(0.118)
Skills	Active Listening	0.060	(0.098)
Knowledge	Clerical	0.059	(0.116)
Abilities	Far Vision	0.054	(0.079)
WorkStyle	Attention to Detail	0.054	(0.093)
Skills	Complex Problem Solving	0.052	(0.088)
Skills	Equipment Selection	0.050	(0.109)
Abilities	Flexibility of Closure	0.049	(0.082)
Skills	Management of Financial Resources	0.049	(0.122)
Abilities	Speech Recognition	0.046	(0.112)
Abilities	Perceptual Speed	0.042	(0.106)
Knowledge	Building and Construction	0.041	(0.102)
Abilities	Information Ordering	0.040	(0.096)
Abilities	Visualization	0.038	(0.110)
Skills	Equipment Maintenance	0.033	(0.103)
Skills	Science	0.030	(0.059)
Abilities	Gross Body Equilibrium	0.025	(0.105)
Skills	Repairing	0.024	(0.103)
Knowledge	Economics and Accounting	0.023	(0.132)
Knowledge	Mechanical	0.021	(0.116)
Knowledge	Customer and Personal Service	0.017	(0.138)
Abilities	Dynamic Flexibility	0.015	(0.112)
Abilities	Sound Localization	0.015	(0.108)
Skills	Operations Analysis	0.012	(0.087)
Knowledge	Medicine and Dentistry	0.012	(0.066)
Abilities	Near Vision	0.011	(0.086)
Abilities	Finger Dexterity	0.010	(0.134)
Abilities	Visual Color Discrimination	0.009	(0.148)
Abilities	Speed of Limb Movement	0.006	(0.098)

Abilities	Extent Flexibility	0.006	(0.111)
Knowledge	Telecommunications	0.002	(0.131)
Knowledge	Biology	0.002	(0.051)
Abilities	Glare Sensitivity	-0.004	(0.113)
Abilities	Explosive Strength	-0.008	(0.078)
Abilities	Gross Body Coordination	-0.020	(0.098)
Knowledge	Sales and Marketing	-0.022	(0.128)
Skills	Troubleshooting	-0.022	(0.114)
Skills	Quality Control Analysis	-0.030	(0.138)
Knowledge	Transportation	-0.032	(0.085)
Abilities	Dynamic Strength	-0.033	(0.102)
Skills	Operation Monitoring	-0.034	(0.097)
Abilities	Stamina	-0.04	(0.096)
Abilities	Manual Dexterity	-0.044	(0.111)
Abilities	Arm-Hand Steadiness	-0.045	(0.104)
Abilities	Spatial Orientation	-0.052	(0.107)
Abilities	Night Vision	-0.057	(0.117)
Abilities	Static Strength	-0.060	(0.099)
Skills	Operation and Control	-0.074	(0.095)
Abilities	Peripheral Vision	-0.075	(0.116)
Abilities	Multilimb Coordination	-0.077	(0.102)
Abilities	Wrist-Finger Speed	-0.078	(0.110)
Abilities	Response Orientation	-0.091	(0.096)
Abilities	Control Precision	-0.092	(0.102)
Abilities	Reaction Time	-0.095	(0.088)
Abilities	Depth Perception	-0.102	(0.114)
Abilities	Rate Control	-0.132	(0.088)

Note.- Estimates of β^s using Brazilian data. Robust standard errors in parentheses.