Full Length Articles

Immigration and occupational comparative advantage☆

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ABSTRACT

Job selection by high-skilled foreign-born workers in the US correlates strongly with country of origin. We use a Fréchet-Roy model of occupational choice to evaluate the causes of immigrant sorting. We find that revealed comparative advantage in the US is stronger for workers from countries with higher education quality in occupations that are more intensive in cognitive reasoning, and for workers from countries that are more linguistically similar to the US in occupations that are more intensive in communication. Our findings hold for immigrants who arrived in the US at age 18 or older (who received their K-12 education abroad) but not for immigrants who arrived in the US as children (who received their K-12 education domestically). We obtain similar results for immigrant sorting in Canada, consistent with origin-country education quality, rather than US immigration policy, being what drives sorting patterns.

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1. Introduction

The sorting of foreign-born workers across occupations in the US labor market correlates strongly with country of origin (Patel and Vella, 2013; Hanson and Liu, 2017).[1] Consider immigrants from China and the Philippines. In 2016, they respectively accounted for a similar 1.5% and 1.2% of the prime-age US population with at least a college education, but represented 12.4% versus 1.2% of those employed as medical scientists and 0.9% versus 11.8% of those employed as licensed practical nurses.[2] Such differential sorting is common (see Appendix Table B.1). Among college-educated US residents, there is strong over-representation of workers from India in computer programming, from South Korea in dental health, and from Pakistan in service-station management, among many related examples.[3]

There is a long history of immigrant groups concentrating in particular lines of work. Recent literature, for instance, documents Vietnamese immigrants specializing as manicurists (Federman et al., 2006), Mexican immigrants working as manual laborers and farm workers (Munshi, 2003; Woodruff and Zenteno, 2007), and Haitian immigrants serving as taxi drivers (Jackson and Schneider, 2011). Such clustering is consistent with the presence of migration networks, which connect less-educated immigrants to specific jobs and thereby reduce costs of entry into a new and unfamiliar labor market (McManus, 1990; Munshi, 2020). What

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[1] In Hanson and Liu (2017), we document that occupational specialization of immigrants in the US by origin country is persistent over time and common across gender groups. In this paper, we turn our attention to the determinants of revealed occupational comparative advantage.

[2] These figures are from the 2014–2018 American Communities Survey. Prime-age workers are those 25 to 54 years old; having a college education means having completed at least four years of college.

[3] Over 2014–2018, immigrants from India were 3.2% of the US college-educated population 25 to 54 years old and 15.5% of computer programmers, immigrants from Korea were 0.9% of this population and 6.0% of dental technicians, and immigrants from Pakistan were 0.3% of this population and 5.7% of service-station managers.

is distinct about the examples cited above is that the jobs involved—medical research, licensed nursing, business management, computer programming—typically require a college degree, which migrants commonly attain in their home countries.[4] Having attained an advanced education and selected into immigration, individuals then appear to choose occupations based in part on where they were born.[5]

In this paper, we use a Fréchet-Roy (1951) framework to evaluate the causes of immigrant sorting across jobs. Perhaps the most obvious force behind sorting is language. When working in the US, immigrants from non-English-speaking countries may have a comparative disadvantage in jobs that are intensive in communication (Peri and Sparber, 2009; Oreopoulos, 2011). A second force, also related to comparative advantage, is the quality of education in the origin country. Countries that excel in math and science training, for instance, may be more likely to produce immigrants who work in STEM fields (Hunt and Gauthier-Loiselle, 2010). A third force behind sorting is the cost of migration. If policy barriers in a destination differ across origin countries, then immigrants from high-migration-cost countries may be more positively selected in terms of skill (Grogger and Hanson, 2011).[6]

The first step in our analysis is to apply a Fréchet-Roy model (e.g., Burstein et al., 2019; Hsieh et al., 2019) to derive a gravity expression for the share of college-educated immigrants from a given origin country who are employed in a given US occupation. These employment shares are a function of wages at the occupation level in the US, and labor productivity, migration costs, and alternative employment opportunities for workers from the origin. By pooling data across origin-country groups and occupations in the US and regressing log employment shares on country-of-origin and occupation fixed effects, we neutralize the importance of alternative employment options, for each national-origin group, and average US wages, for each occupation, in occupational choice.[7] The residual component of these employment shares, which is our focus, is revealed occupational comparative advantage. Importantly, the gravity equation we derive is isomorphic to that obtained from a model in which migration costs are a function of past migrant flows (as in, e.g., Beine et al., 2008; Docquier and Rapoport, 2012; Patel and Vella, 2013), which creates dynamics in migration decisions.

In theory, origin-country revealed comparative advantage by occupation is determined by fundamental comparative advantage and migration costs (which may or may not embody network effects).[8] For more-educated workers, fundamental comparative advantage may be shaped by the quality of a country's educational institutions, where the skills that these institutions impart may vary in importance across jobs (Hunt, 2011; Peri et al., 2015). Russia, whose universities excel in mathematics, produces mathematicians who in turn excel when competing against their US counterparts (Borjas and Doran, 2012). However, its workers may not be equipped to succeed in US managerial or sales-related professions. In a similar vein, whereas on average foreign-born workers with stronger English language skills achieve higher earnings in the US labor market (Dustmann and Fabbri, 2003; Bleakley and Chin, 2004; Hunt, 2015), the return to language ability may be larger in jobs that require stronger communication skills (e.g., management, sales) than in those that do not (e.g., engineering, mathematics) (Chiswick and Taengnoi, 2007). Migration costs may also affect occupational sorting by favoring migrants with higher earnings potential (Lazear, 2021).

Motivated by analysis of comparative advantage in international trade, we model occupational comparative advantage by interacting origin-country attributes with occupation-specific job requirements.[9] Origin country attributes include linguistic similarity with the US (Isphording and Otten, 2014; Melitz and Toubal, 2014), national performance in standardized exams conducted by the Program for International Student Assessment (PISA) (Hanushek and Kimko, 2000; Hanushek and Woessmann, 2011), and geographic distance to the US (Head and Mayer, 2013); occupational requirements include performing tasks that require cognitive reasoning, interpersonal communication, manual effort, and repetitive operations (Autor et al., 2003; Deming, 2017). Additional interactions control for bilateral migration costs not absorbed by origin-country fixed effects. Under common assumptions (i.e., occupations with more immigrants in the past are more attractive to current immigrants, as in Patel and Vella, 2013), network effects modify the interpretation of the regression coefficients, but not the empirical specification.

Our specification will capture the role of comparative advantage in immigrant occupational sorting (i) if workers from countries that score relatively highly in math and science exams excel in jobs that require stronger cognitive skills, and (ii) if workers from English-speaking countries perform relatively well in jobs that require greater face-to-face interaction with customers or co-workers. A substantial body of literature uses PISA exam scores to evaluate the roles of education quality and cognitive skills in

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[4] See Cortés and Pan (2014) on the labor-market consequences of inflows of female nurses from the Philippines for US native-born workers. In our baseline analysis, we focus on male workers, because of zero observed employment for women from smaller source countries in many occupational categories; in the appendix, we expand the analysis to include women.

[5] In the literature, the sorting of less-educated immigrants into specific occupations has a strong spatial dimension, which suggests that localized immigrant job networks, as opposed to origin-country-specific training or labor-market experience, are behind national clustering patterns (Patel and Vella, 2013). By contrast, the instances of sorting among the college-educated foreign born that we document are a US-wide phenomenon.

[6] Related work addresses native-born educational and occupational responses to immigration (Llull, 2018; Burstein et al., 2020), and the tendency of foreign-born workers to experience occupational downgrading in the destination country (Dustmann et al., 2013).

[7] This double-differencing is akin to that used in estimating the gravity model of trade. See, e.g., Head and Ries (2001) and Novy (2013) on the use of double differencing to identify the components of trade costs.

[8] In the Fréchet-Roy framework, fundamental comparative advantage is defined by the location parameters of the Fréchet distributions for worker productivity in the origin countries under consideration.

[9] See, e.g., Romalis (2004), Levchenko (2007), and Chor (2010) for alternative approaches to interacting industry characteristics (e.g., factor intensity, product complexity) and country characteristics (e.g., factor endowments, quality of institutions) to account for comparative advantage when estimating gravity models of international trade. In extended analysis, we incorporate interactions between occupational task intensities and these country characteristics, which has little effect on our baseline results.

economic development (see, e.g., Hanushek and Woessmann, 2011; Woessmann, 2016).[10] Our contribution is to show how origin-country education quality affects the matching of workers to jobs abroad and thereby helps determine the composition of international labor flows.

Other work uses the task intensity of jobs to evaluate how specialization in routine activities affects worker exposure to technological change (e.g., Autor and Dorn, 2013; Goos et al., 2014; Hershbein and Kahn, 2018), how the returns to cognitive and social skills evolve over time (e.g., Beaudry et al., 2016; Deming, 2017; Deming and Noray, 2020), and how immigration affects the US labor-market (Peri and Sparber, 2009, 2011). We show how task intensity affects the matching of more-educated foreign-born workers to occupations and thus competition at the high end of the labor market.

More broadly, our work connects to literature on worker sorting. In theory, the matching of more-skilled workers to more skill-intensive tasks determines worker exposure to international competition (Costinot and Vogel, 2010) and technological change, where skill may be uni-dimensional (Acemoglu and Autor, 2011) or multi-dimensional (Lindenlaub, 2017). In a Fréchet-Roy context, positive sorting explains cross-country differences in agricultural productivity (Lagakos and Waugh, 2013), the labor market impacts of gender and racial discrimination (Hsieh et al., 2019), and the exposure of native-born workers to the arrival of immigrant labor (Burstein et al., 2020). We identify the country characteristics (cognitive, linguistic skills) that complement job requirements (cognitive reasoning, interpersonal communication) in the sorting process, and test for positive sorting in the context of multi-dimensional skills.

Consistent with Fréchet-Roy logic, we find that revealed comparative advantage (defined relative to the average occupation) is stronger in occupations more intensive in cognitive reasoning for countries with higher PISA test scores and in occupations more intensive in interpersonal communication for countries that are more linguistically similar to the US. Comparing countries at the 25th and 75th percentiles of PISA math scores, the higher scoring country would have a 75% higher share of its college-educated immigrant labor in US financial management jobs, which is the occupation at the 75th percentile of intensity in cognitive tasks. Similarly, when comparing countries at the 25th and 75th percentiles of linguistic similarity with the US, the higher scoring country would have a 19% higher share of its college-educated immigrant labor in US executive management positions, which is the occupation at the 75th percentile of intensity in communication tasks.[11]

In interpreting our results as capturing how comparative advantage affects immigrant sorting across jobs, we confront several potential confounds. One is origin-country bias in US immigration policy. If visas for more-educated workers were awarded on the basis of skill alone, then immigrant sorting across jobs would largely reflect origin-country capabilities: immigrants from countries with higher education quality would concentrate in jobs requiring more analytical reasoning, and those from countries with greater facility in English would concentrate in jobs more reliant on communication. In reality, over 2006 to 2014, which spans our sample period, the US granted 65% of permanent residence visas (green cards) to immigrants who were sponsored by family members in the US, 14% to asylees and refugees, and another 14% to immigrants sponsored by US employers (OIS, 2020). Although college-educated immigrants are more likely to enter the US on employment visas than are the non-college educated (Bound et al., 2017; Gelatt, 2020), the preferences used to award green cards could somehow distort visa allocation away from comparative advantage.[12]

To evaluate the potentially confounding effects of US visa policies, we re-estimate our specifications using data on the allocation of foreign and native-born labor across occupations in Canada. Distinct from the US, Canada allocates the majority of its immigration visas using a point system, which favors working-age individuals with more education, more labor market experience, and facility in English or French.[13] Our results for Canada are very similar to our results for the US, which suggests that our findings are not purely a byproduct of US immigration policy and instead capture origin-country strengths.

A second potential confound is the impact of culture and social norms on migrant behavior (e.g., Fernandez and Fogli, 2009). If certain ancestries accord higher social status, say, to having a job in a STEM field, then higher standardized test scores could reflect these values, rather than origin-country education quality.[14] To isolate the impact of being educated in the origin country, we separate the foreign born into those who arrived in the US at age 18 or older, and therefore likely completed their K-12 education in their country of birth, and those who arrived before age 18 (or before age 13), and therefore were educated partly or entirely in the US. Our results on comparative advantage are much weaker for the under-18 (and under-13) arrivals than for the 18-and-older arrivals. When we further limit the sample to US-born individuals and separate them according to their ancestral country of origin, we again find a weaker relationship between origin-country

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[10] Also on the use of PISA exam scores, see Lavy (2015) and Hanushek et al. (2020) on how cross-country differences in student preferences and behavior affect test outcomes; Akyol et al. (2018) and Mogstad et al. (2020) on constructing country performance rankings when using noisy measures of individual ability; and Xiang and Yeaple (2018) on estimating the magnitudes of cognitive and non-cognitive labor skills by country.

[11] For evidence of how the composition of migrants affects regional comparative advantage, see Pellegrina and Sotelo (2021) and Hanson (2021).

[12] Data from the New Immigrant Survey for 2003 show that the fraction of immigrants with a college education or advanced degree is 82% of those entering on employer-sponsored visas, 37% of those entering as spouses of US residents, and 33% of those entering as refugees or asylees (Gelatt, 2020).

[13] See Borjas (1993) on the origins of differences in Canadian and US immigration systems. Antecol et al. (2003) and Kaushal and Lu (2015) document that relative to Canada, US admissions are biased against skills-based immigration and in favor of non-immediate relatives of US residents.

[14] Equivalently, amenity values attached to occupations may vary by origin country. In our model, we show how such origin-country-specific occupational amenities may affect occupation choice.

comparative advantage and occupational sorting by ancestry. These results suggest that exposure to origin-country educational institutions shapes the occupational sorting of migrant labor abroad.[15]

In Section 2, we outline our theoretical and empirical framework; in Section 3, we describe our data and patterns of immigrant sorting by occupation; in Sections 4 and 5, we present our empirical findings; and in Section 6, we conclude.

2. Model

We use a Roy model of occupation choice to derive our estimating equation. In the model, workers from each origin country s choose a destination country d in which to reside and an occupation o in which to work. The model structure implies that the allocation of workers across destinations and occupations is a function of national comparative advantage and bilateral migration costs.[16] We first present a model without network effects, and then show how including such effects yields an identical estimating equation, though one whose parameters have an enhanced meaning.

2.1. Labor supply

Consider the migration and occupation choices for labor-market group s (e.g., college-educated men born in China). Within each group, there is a continuum of workers i. Each worker independently draws a vector of productivity values $a_{d,o}^{i,s}$ across destination-countries d and occupations o from a univariate Fréchet distribution, which has the following CDF,[17]

$$F\left(a_{d,o}^{i,s} \le x\right) = \exp\left\{-\left(\frac{x}{T_{d,o}^s}\right)^{-\theta}\right\}, \quad \theta > 1.$$

The distribution has two parameters, θ and $T_{d,o}^s$. With $T_{d,o}^s$ fixed, a larger θ corresponds to a smaller within-group dispersion of productivity. $T_{d,o}^s$ is the scale parameter, where a larger value corresponds to a higher level of average group productivity and greater within-group productivity dispersion. With the dispersion parameter θ assumed constant across origins s, destinations d, and occupations o, the scale parameters define fundamental comparative advantage of source countries across occupations in each destination.

We assume that migration is costly, where $c_{d,o}^s$ is the fraction of earnings lost for a worker from origin s to live in destination d and work in occupation o.[18] The migration cost $c_{d,o}^s$ captures all sources of migration frictions, including the monetary cost of moving to the destination (which likely varies by origin-destination pair but not by occupation), the cost of securing a visa for the destination (which because of rules for allocating visas likely varies by origin-destination and possibly by occupation), and the cost of finding a job once in the destination (which because of migration networks, and visa-based work restrictions likely varies by origin-destination and possibly by occupation).[19] We denote $\tau_{d,o}^s \equiv 1 - c_{d,o}^s$ as the fraction of earnings that a worker takes home. Initially, we treat migration costs as independent of network effects and later allow them to be a function of past migration flows. We also elaborate on the interpretation of $\tau_{d,o}^s$ to include other dimensions of perceived differences in job attributes across occupations by origin country.

2.2. Labor allocation

Workers choose a country of residence and an occupation in order to maximize their perceived take-home wage, $\tau_{d,o}^s \cdot w_{d,o} \cdot a_{d,o}^{i,s}$, where $w_{d,o}$ is the wage per efficiency unit of labor in occupation o in destination d. Given the assumption of Fréchet distributed productivities, the fraction of s workers who live in country d and work in occupation o is

$$\Pi_{d,o}^s = \frac{\left(T_{d,o}^s \tau_{d,o}^s w_{d,o}\right)^\theta}{\sum_{d',o'} \left(T_{d',o'}^s \tau_{d',o'}^s w_{d',o'}\right)^\theta} \tag{1}$$

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[15] In Appendix E, we use quantitative analysis to evaluate the general equilibrium implications of alternative US immigration policies. We find that if the US were to reallocate visas from low PISA score to high PISA score countries—e.g., to move closer to Canada's point system for immigration—US immigration from East Asia would increase while immigration from Latin America would decrease. This would in turn lead US employment to expand in STEM-related occupations and contract in most other occupations.

[16] Aggregating across these allocations for a given destination country (e.g., the US or Canada) allows us to evaluate counterfactually how changing bilateral migration costs would affect earnings in the destination, which we do in the appendix.

[17] Alternatively, we could allow Fréchet productivity draws to be correlated across occupations and destination countries, with differing cross-occupation and cross-destination correlations. Any such generalization of the Fréchet productivity distribution would produce an estimating equation that is isomorphic to ours, as long as we assume a common elasticity of substitution in labor supply at the occupational level.

[18] The assumption of multiplicative migration costs is common in the literature on the self-selection of immigrants (see, e.g., Borjas, 1987; Chiquiar and Hanson, 2005).

[19] Because of occupational licensing, it is not necessarily true that $\tau_{d,o}^d = 1$ for all o. On occupational licensing for foreign-born workers, see Han and Kleiner (2016) and Cassidy and Dacass (2021); on occupational discrimination against foreign-born workers, see Oreopoulosa (2011).

Conditional on having chosen to live in destination d, the fraction of workers from origin country s who work in occupation o is then

$$\Pi_{o|d}^s = \frac{\Pi_{d,o}^s}{\sum_{o'}\Pi_{d,o'}^s} = \frac{\left(T_{d,o}^s \tau_{d,o}^s w_{d,o}\right)^\theta}{\sum_{o'}\left(T_{d,o'}^s \tau_{d,o'}^s w_{d,o'}\right)^\theta} \tag{2}$$

In the empirical analysis, we study the allocation of college-educated workers from each origin country across occupations in two destination countries, the US and Canada. In the model underlying (2), we do not allow for migration networks, which may create path dependence in immigrant occupational choices. In Section 2.5, we introduce such networks, which delivers an equation that is isomorphic to (2).

2.3. Sorting with multi-dimensional skills

In standard applications of Fréchet-Roy, skill is one dimensional: a worker's productivity in each occupation is given by a scalar function of a Fréchet draw. In our application, we follow Lindenlaub (2017) and assume that worker skill is multi-dimensional.[20] Workers vary in their cognitive skill (i.e., the ability to solve difficult problems) and linguistic proficiency (i.e., facility in languages that are spoken in the US), where these skills affect task-specific productivity based on task-specific parameters. We model positive sorting on multi-dimensional skills to provide a theoretical interpretation of our empirical results.

To motivate our approach, consider empirical evidence on the labor market return to education across occupations differentiated by their task intensity. Using the Princeton Data Improvement Initiative survey, Autor and Handel (2013) show that college educated workers are much more likely to perform abstract tasks on the job than are non-college-educated workers.[21] This regularity is consistent with the positive sorting of workers across jobs, where educational attainment is the relevant skill for abstract tasks. Holding education constant, workers in more abstract-task-intensive jobs earn higher wages,[22] which is consistent with higher ability workers sorting into jobs more intensive in abstract tasks (i.e., positive sorting in unobserved skill). We interpret these results as supporting our assumption that workers with stronger cognitive skills will sort into jobs more intensive in cognitive tasks. Regarding language, Dustmann and Fabbri (2003) and Bleakley and Chin (2004) find that immigrants with better English language skills earn higher wages in the UK and US labor markets, respectively, while Peri and Sparber (2009) find that in the US less-educated immigrants from non-English speaking countries are less likely than US natives to be employed in communication-intensive occupations. These results are consistent with positive returns to ability in the native language and with positive sorting based on language ability.

To operationalize positive sorting in multi-dimensional skill in our context, we assume that the group-level occupational efficiency $T_{d,o}^s$ (e.g., the capability of college graduates born in China in medical science) is an exponential function of skills and task intensity. Occupational efficiency for each origin s in occupation o and in destination d is given by,

$$T_{d,o}^s = \prod_{j \in \mathcal{J}} \prod_{k \in \mathcal{K}} \exp\left(\beta_{j,k} \times X_j^s \times Y_k^o\right). \tag{3}$$

Eq. (3) includes two types of skill measures, cognitive and language skills, indexed by $j \in \mathcal{J} = \{cog, com\}$; and four types of occupational task intensities (cognitive, communication, routine, and manual), indexed by $k \in \mathcal{K} = \{cog, com, rou, man\}$.[23] X_j^s is the scalar measure skill type j for origin s, while Y_k^o is the scalar measure of intensity in task j for occupation o[24]; for example, X_{cog}^s is cognitive skill for immigrants from country s (measured using the PISA math score), and Y_{cog}^o is cognitive task intensity for occupation o (measured using O*NET). The combination $\beta_{cog,cog} \times Y_{cog}^o$ is the marginal productivity that converts cognitive-skill into cognitive-task output in occupation o. Similarly $\beta_{cog,com} \times Y_{com}^o$ is the marginal productivity that converts cognitive-skill into communication-task output in occupation o. The aggregator in (3) is the basis for our empirical specification.

The variation in group-level occupational productivity $T_{d,o}^s$ is driven by differences in the cognitive and linguistic skills of workers. Because we lack country-level measures of routine and manual skills, we abstract from their role in occupational sorting. Our empirical analysis is thus informative about sorting in two dimensions—cognitive and linguistic skill—and silent about sorting in other dimensions. The omission would be innocuous if the average skills of college-educated workers in routine and manual do not vary across origin countries for immigration — in this case the omitted interaction terms would be absorbed by the

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[20] Lindenlaub's model addresses two-side matching between firms and workers, where firms care about individual worker productivity. In her case, the matching function is characterized by a differential equation. In our model, sorting occurs on the labor supply side only. Implicitly, firms care not about individual worker productivity but the total efficiency units of labor they hire.

[21] In these data, abstract task intensity is the first principal component across four task measures: length of longest document typically read as part of the job, frequency of mathematics tasks involving high school or higher mathematics, frequency of problem-solving tasks requiring at least 30 min to find a good solution, and proportion of workday managing or supervising other workers.

[22] These results hold for abstract task intensity defined either in the PDII or O*NET.

[23] Because of the data availability, the dimension of skills is smaller than that of task intensity.

[24] In the empirical analysis, the level terms for these intensities are absorbed into the occupation fixed effects. We assume these intensities are the same in the US and Canada. Atalay et al. (2018) use a Cobb-Douglas structure to model occupational efficiency units as a bundle of skills, similar to us.

occupational fixed effects; or if routine and manual skills are (pairwise) orthogonal to cognitive and linguistic skills — in this case, omitting routine and manual skill related interactions does not change the covariance between the regression residual and our main regressors, condition on occupational fixed-effect. To address the potential for omitted variable bias, in Section 4.4.3 we include a rich set of interactions between country characteristics and occupation task intensity, which yields results that are very similar to our baseline.

Unlike the case of uni-dimensional skill, workers in our context cannot be fully ranked by their skill levels. Leveraging results in Lindenlaub (2017), we state the conditions necessary for positive sorting of workers across occupations by skill in the case of two-dimensional skills (cognitive and linguistic skill). Let the occupational choice probability (i.e., the assignment function) be $\Pi\left(X_j^s, Y_k^o\right)$, which we assume is continuous and twice differentiable. Following Lindenlaub (2017), we have positive sorting in two-dimensional skills if there is positive sorting along each individual dimension of skill, and sorting within the "natural" dimension of each skill is more pronounced than across the "natural" dimensions of the skills. Stated formally, positive sorting requires,

(A) $\dfrac{\partial^2 \Pi\left(X_j^s, Y_k^o\right)}{\partial X_{cog}^s \, \partial Y_{cog}^o} > 0,$

(B) $\dfrac{\partial^2 \Pi\left(X_j^s, Y_k^o\right)}{\partial X_{com}^s \, \partial Y_{com}^o} > 0,$

(C) $\begin{vmatrix} \dfrac{\partial^2 \Pi\left(X_j^s, Y_k^o\right)}{\partial X_{cog}^s \, \partial Y_{cog}^o}, & \dfrac{\partial^2 \Pi\left(X_j^s, Y_k^o\right)}{\partial X_{cog}^s \, \partial Y_{com}^o} \\[3ex] \dfrac{\partial^2 \Pi\left(X_j^s, Y_k^o\right)}{\partial X_{com}^s \, \partial Y_{cog}^o}, & \dfrac{\partial^2 \Pi\left(X_j^s, Y_k^o\right)}{\partial X_{com}^s \, \partial Y_{com}^o} \end{vmatrix} > 0.$

Lindenlaub (2017)'s concept of multi-dimensional sorting is based on matching on observables. In her case, there is a one-to-one matching between workers and occupations (or full specialization). Our model has (unobserved) idiosyncratic Fréchet distributed productivities for each national-origin group of college-educated labor. Our definition thus extends Lindenlaub (2017) to a probabilistic case (or partial specialization).

To interpret the above conditions, note that (A) and (B) require that there be positive sorting along each of the single natural skill-task dimensions: workers from countries with stronger cognitive skills are more likely to choose cognitive-task-intensive occupations (X_{cog}^s-to-Y_{cog}^o), and workers from countries with stronger linguistic skills (vis-á-vis the US) are more likely to choose communication-task-intensive occupations (X_{com}^s-to-Y_{com}^o). These conditions follow the probabilistic version of uni-dimensional sorting defined in Costinot and Vogel (2015), in that they imply that the Monotone Likelihood Ratio Property holds in each skill dimension considered individually. Condition (C) distinguishes the multi-dimensional and uni-dimensional cases. For positive sorting to occur, sorting *within* the natural dimensions (characterized by the product of diagonal elements) must be more pronounced than sorting *across* the natural dimensions (characterized by the product of off-diagonal elements).

2.4. The estimating equation and testable implications

We next use (2) to derive an estimating equation for the determination of the log share of workers born in source *s* who are living in *d* and working in occupation *o*,

$$\log \Pi_{old}^s = \theta \log T_{d,o}^s + \alpha_s + \alpha_o + \theta \log \tau_{d,o}^s. \tag{4}$$

The term, $\alpha_s \equiv -\log \sum_{o'} (T_{d,o'}^s \tau_{d,o'}^s w_{d,o'})^{\theta}$, is a source-country fixed effect that captures average employment opportunities for *s* workers in other occupations in *d*; note that this term will also absorb any migration costs (including network effects) that are specific to origin *s* and common across occupations in *d* (e.g., financial and psychic costs of moving, visa application costs). The term, $\alpha_o \equiv \theta \log w_{d,o}$, is an occupation fixed effect, which absorbs the average price per efficiency unit of labor in *d* for occupation *o*; this term also absorbs any occupational licensing costs specific to *o* that are common to workers regardless of their birth country. The final term, $\theta \log \tau_{d,o}^s$, captures bilateral frictions that affect migration and occupation choices. Below, we discuss how we specify the determinants of $T_{d,o}^s$ and $\tau_{d,o}^s$ in (4).

In applying (4), we examine differences in worker sorting across occupations by source country of immigration. Since we consider worker sorting in the destination only, our analysis is silent about variation in the degree of positive selection of workers by skill across origin locations. As is well-known, the Fréchet-Roy model delivers the prediction that the degree of positive selection

(i.e., the skill difference between immigrants and workers who remain at home) is decreasing in the fraction of the population that chooses a given occupation and destination. Bryan and Morten (2019) find support for this prediction when analyzing internal migration in Indonesia. For international migration to the US, Lazear (2017) finds that immigrants from countries that send a smaller fraction of their population to the US have higher earnings in the US when compared to immigrants from other countries.

In a regression context, $\tau_{d,o}^s$ stands in not just for migration costs but for any other occupational attribute, other than worker productivity, that affects job choice differentially by origin country. Such factors could include occupation-specific amenities, whose values have an origin country component (e.g., if the social status attached to occupations varies by origin). If these unobserved amenities are correlated with $T_{d,o}^s$, our estimation results may be subject to omitted variable bias. In Section 4.3, we address this issue by splitting the sample according to immigrant age of arrival. This helps us separate the effects of exposure to origin-country educational institutions from those of exposure origin-country social values.

Substituting Eq. (3) into (4), we have

$$\log \Pi_{o|d}^s = \theta \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \left[\beta_{j,k} \times X_j^s \times Y_k^o \right] + \alpha_s + \alpha_o + \theta \log \tau_{d,o}^s. \tag{5}$$

In the empirical analysis, we will measure Y_k^o using data on occupational task intensities. The testable implications of positive sorting with two skill dimensions (cognitive and linguistic skills) are

(A′) $\beta_{cog,cog} > 0$

(B′) $\beta_{com,com} > 0$

(C′) $\begin{vmatrix} \beta_{cog,cog} & \beta_{com,cog} \\ \beta_{cog,com} & \beta_{com,com} \end{vmatrix} = \beta_{cog,cog}\beta_{com,com} - \beta_{com,cog}\beta_{cog,com} > 0.$

Note that we add the interaction terms, X_{cog}^s-to-Y_{rou}^o, X_{cog}^s-to-Y_{man}^o, X_{com}^s-to-Y_{rou}^o, and X_{com}^s-to-Y_{man}^o, as regressors, which allows us to control for sorting across the natural dimensions of these other skill types (despite our not having measures of country-level supplies of manual or routine skills). We further interact occupational task intensities with origin-country geographic distance to the US, which provides additional controls for migration costs that may be specific to the occupation and origin country combination.

2.5. Path dependence and the estimating equation

Evidence on bilateral migration is consistent with network effects, in which migration costs today are a function of migration patterns in previous time periods (Beine et al., 2008; Patel and Vella, 2013). How would the presence of migration networks change our estimation approach? In our context, suppose that migration costs are related to occupational employment patterns for immigrants in the previous period. In particular, assume that $\log \Pi_{o,t|d}^s$ follows an AR(1) process, resulting from the following structure for migration costs:

$$\tau_{d,o,t}^s = \left(\Pi_{o,t-1|d}^s \right)^\rho \exp\left(\varepsilon_{d,o,t}^s \right), \qquad \rho \in (0,1) \tag{6}$$

where $\Pi_{o,t-1|d}^s$ is the share of workers from source country s who worked in occupation o in the previous period, conditional on living in country d.[25] The logic here is that the higher is $\Pi_{o,t-1|d}^s$, meaning higher past s-group network intensity in occupation o in country d, the easier it is for s workers to enter that occupation in the destination today (Munshi, 2003). The parameter ρ, which is positive in the case of network effects, is the elasticity of the take-home wage rate with respect to previous migrant exposure to occupation o, while $\varepsilon_{d,o,t}^s$ captures time-varying barriers other than migration networks that affect occupational choice.

Assuming that $T_{d,o}^s$ is constant over time, we can use (6) to rewrite (5) as,

$$\log \Pi_{o,t|d}^s = \frac{\theta}{1-\rho} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \left[\beta_{j,k} \times X_j^s \times Y_k^o \right] + \alpha_{s,t} + \alpha_{o,t} + \sum_{k=0}^t \rho^k \varepsilon_{d,o,t-k}^s. \tag{7}$$

There are three takeaways from (7). First, assuming that $\rho \in (0,1)$, the estimating equation in presence of migration networks (where $\tau_{d,o,t}^s$ follows the functional form as given in (6)) is isomorphic to (5). Second, the regression coefficients on $X_j^s \times Y_k^o$ change from being the long-run elasticity of occupational employment with respect to occupational productivity, θ, to being

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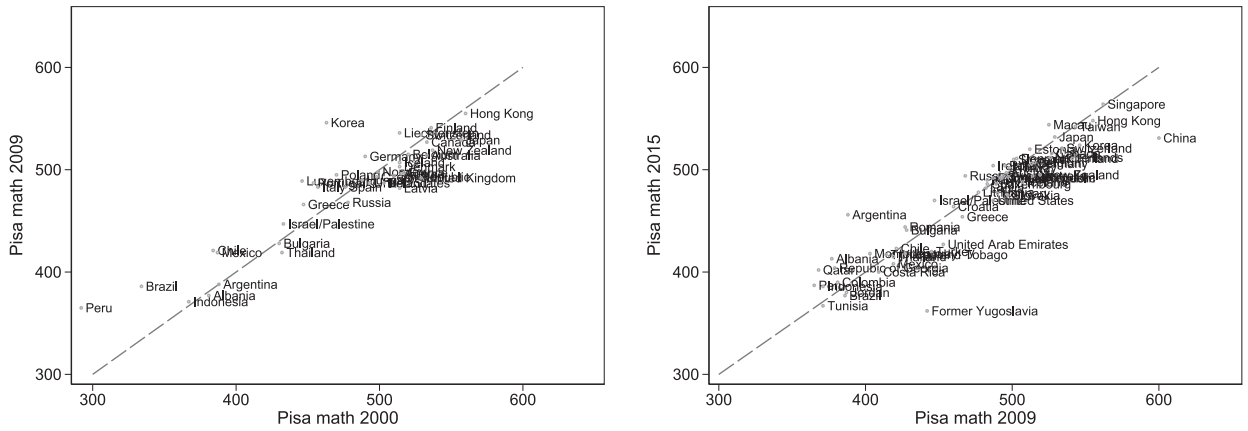[25] We thank Eduardo Morales for suggesting this exercise.

Fig. 1. PISA math scores in 2000 and 2009 (left panel), 2009 and 2015 (right panel).

this value divided by the strength of path dependence, as captured by $1 - \rho$. Third, as long as idiosyncratic shocks to migration at any time t are independent of $T_{d,o'}^s$ then omitted variable bias is unlikely to create an endogeneity problem in the estimation. We proceed with the estimation, mindful that migration networks may condition the interpretation of the estimated regression coefficients.[26]

3. Data

Our goal is to estimate Eq. (5) for foreign-born college-educated workers in the US and Canada and to use the results to evaluate the importance of comparative advantage in foreign-born worker sorting across occupations. In this section, we discuss how we measure origin country cognitive and linguistic skills, occupational requirements in specific tasks, the allocation of workers across occupations, and other details. We then present graphical evidence on comparative advantage in immigrant sorting across occupations.

3.1. Origin country cognitive and linguistic skills

Following recent literature on the contribution of education to economic development (see, e.g., Hanushek and Woessmann, 2011; Woessmann, 2016), we measure cognitive skill in origin countries using PISA exam scores. PISA exams are international assessments of the scholastic performance of 15-year-old students in mathematics, science, and reading. They are widely used to measure national educational quality (e.g., Guiso et al., 2008; Fryer and Levitt, 2010; Bharadwaj et al., 2012). The exams, which are conducted by the Organization for Economic Cooperation and Development, have been administered every three years since 2000. Participation by countries has varied over time, rising from 41 countries in 2000 to 70 countries in 2009 and to 75 countries in 2015. By summarizing cross-country differences in academic performance, the exams provide information about the success of national educational institutions in training students to reason analytically.

PISA exam scores are strongly positively correlated across math, science, and reading assessments. In 2012, the correlation between country average math and science scores was 0.97, between average math and reading scores was 0.96, and between average science and reading scores was 0.98. These patterns suggest that the exams capture the general ability to solve problems, rather than aptitude in specific subjects. For this reason, we interpret PISA scores as a measure of cognitive skill. We use math scores in our analysis; results are unchanged when using science or reading scores, instead. Across schools, PISA scores are positively correlated with the amount of time that students spend in instruction, although this association is weaker in lower income countries (Lavy, 2015). Across countries, PISA scores are positively correlated with the rate of time preference and per capita GDP growth, but not with education spending per student (Hanushek et al., 2020). Within the US, origin-country PISA scores are positively correlated with the labor market returns to education when estimated separately for immigrants by country of birth (Schoellman, 2012).

It is also true that PISA exam scores are strongly persistent over time, as seen in Fig. 1. The correlation between average math scores in 2000 and 2009 (40 countries) is 0.91, while that for 2009 and 2015 (62 countries) is 0.93. Such persistence suggests, not unreasonably, that national education quality changes slowly over time. We exploit this persistence to increase our sample size. Because not all countries participated in the tests in all years, we average exam scores over the 2000 to 2015 period, which

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[26] Alternatively, suppose that $\log T_{d,o}^s$ follows a AR(1) process, where $\log T_{d,o,t}^s = \lambda \log T_{d,o,t-1}^s + \eta_{d,o,t}^s$. Incorporating this expression into (5), the parameter on the summation of interaction terms becomes $\frac{\theta}{1-\lambda}$, which is the long-run occupational employment elasticity (θ) divided by the strength of path dependence in productivity $(1 - \lambda)$. An AR(1) process for productivity can be micro-founded following literature on knowledge diffusion (Kortum, 1997; Cai et al., 2022). In this setting, $\eta_{d,o,t}^s$ is the idiosyncratic shock to knowledge diffusion for country s. We obtain unbiased coefficient estimates as long as, conditional on geographic distance to the US, the shock is uncorrelated with country education quality and linguistic distance to the US.

produces a sample of 69 countries for which we have data on foreign-born workers in the US. If international migrants are positively selected in terms of education or other determinants of skill (Grogger and Hanson, 2011), then average scores in a country may not be indicative of the skills of workers who migrate abroad. To account for positive selection, we also report results using the 75th and 90th percentiles of PISA exam scores, averaged over the years 2009, 2012, and 2015, for which these moments are available. When using these measures, our sample is 61 countries.

There are well-known limitations of PISA exam scores. One is that students who participate in the tests may not be nationally representative. Although most countries administer PISA exams on a nationwide basis, others limit exams to wealthier or better-educated regions (Sands, 2017). For example, in 2012 China only tested students in Shanghai (though in 2015 it expanded tests to include the five largest provinces). Using higher moments of PISA exam scores to measure cognitive skill (e.g., scores at the 90th percentile) may help attenuate the effects of cross-country differences in student testing protocols. A second limitation is that some origin countries, including India, do not participate in the PISA exams and therefore are excluded from the analysis.

An alternative source for data on country education quality is the Trends in International Mathematics and Science Study (TIMSS). Because TIMSS only covers 50 countries and disproportionately represents the Middle East, it is less suitable for our analysis. PISA exams cover a larger number of countries and have stronger representation among countries in Latin American and East and Southeast Asia. Among the 42 countries for which both PISA and TIMSS math scores are available, the correlation in average scores is 0.83.[27]

To measure linguistic proximity between the US and Canada and origin countries for immigration, we use data from Melitz and Toubal (2014).[28] They construct linguistic proximity between countries using the Automatic Similarity Judgement Program (ASJP) from the Max Planck Institute, which transcribes 40 common words into phonetic script (ASJP code) for each major language and counts the number of phonetic changes that separate each word for a large number of language pairs. For instance, Table 1 shows that whereas one phonetic change separates the English and German words for "you", two phonetic changes separate the English and Chinese version of the word; similarly, whereas three changes separate the English and German words for "name", five changes separate the English and Chinese versions of the word. The average number of changes across the 40 words is a measure of linguistic distance between two languages. To calculate linguistic proximity between a pair of countries, Melitz and Toubal (2014) use the population-weighted average of language-to-language linguistic proximity, where the weights are the products of population shares for the two most commonly spoken languages in each country. The appeal of this approach for measuring linguistic proximity, as opposed to commonly used measures such whether two countries share an official language, is that it captures differences between countries in how words are pronounced. Such differences are likely to be important when it comes to performing communication-intensive tasks on the job. The correlation across countries between PISA math scores and linguistic proximity to the US is 0.17.

As a proxy for migration costs, we use bilateral geographic distance from CEPII.[29] We interact bilateral distance with the full set of occupational task intensities, to account for differential sorting of migrants across occupations based on physical migration costs. Origin country fixed effects in the regression helpfully absorb bilateral migration costs that are common across college-educated workers from a given birth country.

3.2. Occupation task intensity

Recent literature on how technology, globalization, and other shocks affect labor-market outcomes differentiate occupations according to their task intensities and skill requirements (e.g., Autor et al., 2003; Goos and Manning, 2007; Autor and Dorn, 2013). If we know which tasks are performed by which types of workers, we can evaluate how changes in the demand for tasks or the supply of skills affects wages and employment across occupations. To measure task requirements, researchers frequently use the US Department of Labor's Dictionary of Occupational Titles (DOT) or its successor, the Occupational Information Network (O*NET). Because in both the DOT and O*NET the scale of intensity for individual tasks is unknown (Acemoglu and Autor, 2011), it is unclear which data source is a better guide for measuring occupational tasks requirements. To compensate, we utilize both DOT and O*NET-based measures of task intensity in our analysis.

Our O*NET measures of task intensity by occupation follow Deming (2017). Cognitive task intensity is the average of mathematical reasoning ability, mathematics knowledge, and mathematics skill; routine task intensity is the average of the degree of automation and importance of repeating the same tasks; manual task intensity is the average of assisting and caring for others, and service orientation; and communication task intensity is the average of social perceptiveness, coordination, persuasion, and negotiation.

Using the fourth edition of the DOT, we measure cognitive, routine, manual, and communication task requirements by occupation. The first three measures, which we take from Autor et al. (2003), identify cognitive (or abstract) tasks as those involving abstract problem solving, and creative, organizational, and managerial tasks; routine tasks as routine, codifiable cognitive, and manual operations that follow explicit procedures; and manual tasks as those requiring non-routine manual operations that in turn require physical adaptability. We denote these measures as Y_{cog}^{o}, Y_{rou}^{o}, and Y_{man}^{o}. Following Shu et al. (1996), we measure

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[27] In previous work, Hanushek and Kimko (2000) combine multiple tests of student achievement in mathematics and science conducted over 1960 to 1990. Their combined sample has 39 countries.

[28] See Isphording and Otten (2014) on how greater linguistic distance and impedes language acquisition among immigrants in Germany and the US.

[29] Our analysis uses the CEPII variable *diswt*, which measures bilateral distance weighted by countries' internal population distributions and cross-city distances.

Table 1

Examples of ASJP Codes for English, German, and Chinese.

Word	English ASJP code	Germany ASJP code	linguistic distance	Chinese ASJP code	linguistic distance
you	yu	du	1	ni	2
name	neim	nome	3	minci	5

Linguistic distance is the minimum number of changes in ASJP codes needed to translate words between languages (e.g., to move from "neim" (English ASJP code for "name") to "nome" (German ASJP code), one needs three steps: change the letter "e" to "o", delete the letter "i", and add letter "e" to the end).

communication task intensity in the DOT using the variable "talk," which indicates demands for listening and speaking on the job; we denote it as Y_{com}^o.[30]

Whereas the DOT measure of communication task intensity emphasizes speaking and listening on the job, the O*NET measure is a broader concept that emphasizes the use of social skills. Nevertheless, O*NET and DOT measures of task intensity are high correlated for cognitive and communication tasks (0.73 and 0.77, respectively), though the measures are less highly correlated for routine tasks and manual tasks (0.20 and 0.22, respectively). We obtain similar results for the two sets of measures. Since neither DOT nor O*NET variables have a natural scale, we compute the percentile ranking of each task using IPUMS occ1990 codes and weight by hours worked to construct percentile measures for our 29 occupational categories. Further details are presented in Appendix A.

3.3. Employment of foreign-born workers in the US and Canada

Our analysis uses data on the employment of foreign-born workers in two destination countries, the US and Canada. For each country, we define the sample to be prime-age workers (25 to 54 years old), who have at least four years of college education, who earn positive wages, and who do not reside in group quarters. We restrict the sample to men for the main analysis and report results for women in the appendix.

Using Canada as a comparator for the US is based on the idea that the two countries differ in how they admit college-educated immigrants. If they do, then, plausibly, commonalities by origin country in how migrants choose occupations in the two destination countries would reflect commonalities among the migrants, rather than commonalities in how the countries chose whom to admit. Immigrants may obtain a US green card in one of two ways (Antecol et al., 2003). The first is by being the immediate relative of a US citizen, whose admissions are uncapped; the second is by qualifying for the annual allotment of immigration visas, which are given in fixed number to other family members of US residents, immigrants sponsored by a US employer, aslyees and refugees, and immigrants in other categories.[31] To obtain an immigration visa in Canada, one must qualify for skills-based admissions according to a point system (which rewards being more educated, more experienced, English or French speaking, young, and entrepreneurial); as the immediate family member of a Canadian resident; or on humanitarian grounds (Kaushal and Lu, 2015).

Over 2006 to 2014, skills-based visas accounted for 14.4% of US admissions and 57.5% of Canadian admissions, while family-based visas represented 65.5% and 28.1% of US and Canadian admissions, respectively (CIC, 2014; OIS, 2020). From the 1990s to the 2000s, Canada's admissions became more skill biased, relative to the US, as the country modified its point system to reward education and labor-market experience more heavily (Kaushal and Lu, 2015). For our purposes, such differences would not matter if college-educated immigrants in the US were primarily admitted on employer-sponsored visas, whose allocation may resemble Canada's point system. But this does not appear to be the case. Because the US reserves so many visas for family members of US residents, these visas dominate among admissions of the college-educated, too. In the New Immigrant Survey, just 33.0% of US college-educated immigrants obtaining a green card in 2003 where admitted on an employer-sponsored visa (Gelatt, 2020). Most of the rest entered on family visas.

For US employment data, we use the three-year American Community Survey (ACS) sample for 2011 to 2013. Our choice of this time period is to match the data we have available for Canada. We measure employment as the share of total hours worked for a given origin-country group in a given occupation.[32] We group detailed occupations into 29 categories based on similarity in occupational task requirements. Appendix Table B.2 lists the occupation categories and displays their DOT and O*NET task intensities.

Our data for Canada are from the 2011 National Household Survey (NHS). Although micro data were unavailable, we obtained from Statistics Canada tabulations of total hours worked by occupation and country of birth for college-educated men 25 to

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[30] First, we match the 3886 DOT occupations to the 327 IPUMS OCC1990 occupations in our data (using data for 1970 as a crosswalk). Second, we aggregate occupations that are similar in their task contents to our 29 aggregate occupational categories. We proceed similarly when using O*NET data.

[31] For family-sponsored visas in the US, it is the strength of one's familial ties to a US citizen or non-citizen resident that matters for qualification. One's skill is irrelevant (beyond the low bar of being able to demonstrate that one will not be become a public charge after gaining entry to the country).

[32] The weight of each individual in the count of hours worked is given by,

$$\frac{\text{Census sampling weight} \times \text{weeks worked} \times \text{usual hours per week}}{2000}$$

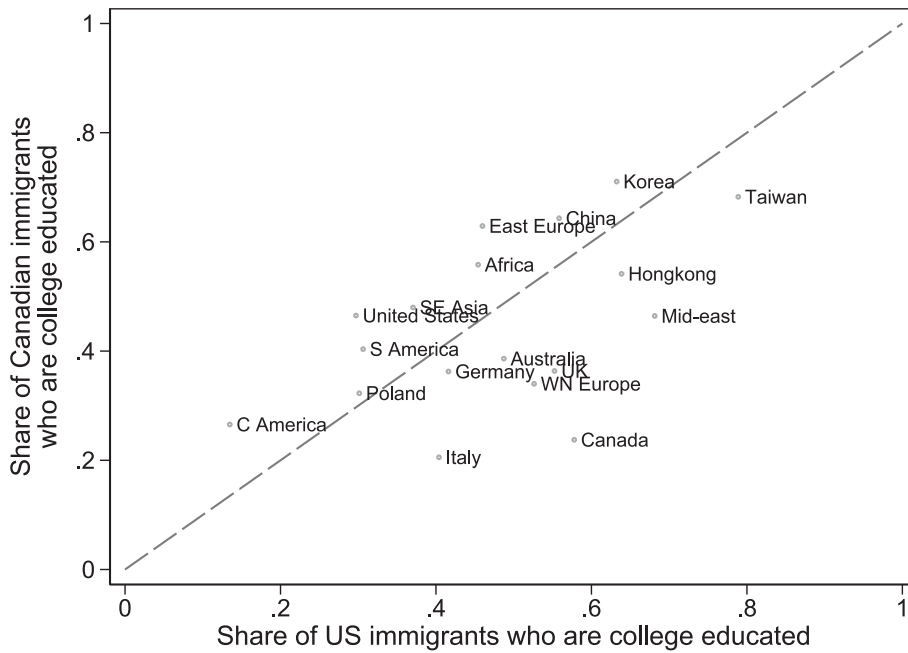where the value for weeks worked is the mid point of the interval reported in IPUMS.

Fig. 2. Share of prime-age foreign-born male workers with at least a college education in Canada (2011) and the US (2011−2013), by origin-country region.

54 years of age. Because for some origin countries the Canadian Census reports immigrant country of birth at a geographically aggregated level, we cluster origin countries into 22 regions. Canada classifies occupations according to a four-digit National Occupational Classification (NOC) code. We aggregate 4-digit NOC codes to match as closely as possible our 29 US occupation categories.[33] We then match DOT and O*NET task variables to these occupations.

To evaluate the degree of similarly in education levels of immigrants in the US and Canada, Fig. 2 plots the shares of adult male immigrants (25 to 54 years old) with at least a college education by region of birth for the two countries in 2010. Most origin regions lie close to the 45-degree line, indicating similar patterns of college attainment among immigrants by region of birth in the two destinations. Using data for 1980, Borjas (1993) documents a corresponding similarity in the educational attainment of immigrants by birth region in the US and Canada. Despite very different immigration policy regimes, it appears that the US and Canada attract individuals with concordant levels of educational attainment by origin country and have done so for the last several decades.

3.4. Preliminary evidence

Before turning to the regression analysis, we present graphical evidence on occupational comparative advantage. We plot a double difference, which is the log ratio of workers born in origin s (e.g., college-educated men born in China) and workers born in destination d (e.g., college-educated men born in the US) who are employed in occupation o (e.g., computer programming) minus the equivalent log ratio of the employment shares for the two groups of workers in some base occupation o', against origin-country average PISA math scores. In order for this comparison to be insensitive to the choice of base occupation o', we construct the denominator $\frac{\Pi_{o'ld}^s}{\Pi_{o'ld}^d}$ using the geometric mean over all occupations, such that,

$$\frac{\Pi_{o'ld}^s}{\Pi_{o'ld}^d} = \exp\left[\frac{1}{\dim(o)} \sum_o \log \frac{\Pi_{old}^s}{\Pi_{old}^d}\right]. \tag{8}$$

Fig. 3 includes four occupations: two are among the top-ranked in terms of DOT or O*NET cognitive task intensity− scientists and mathematicians and computer software developers; and two are ranked toward the bottom−salespersons and high-skill clerical workers. For the cognitive-task-intensive occupations, we see a strong positive correlation between immigrant specialization and origin-country PISA scores: foreign-born workers from countries whose students score more highly on PISA exams are more likely to specialize in occupations that are intensive in cognitive reasoning (precisely estimated slope coefficients of 0.007 in panel (a) and 0.005 in panel (b)). We see no such correlation between PISA scores and immigrant specialization in sales or clerical work (imprecisely estimated slope coefficients of 0.002 in panel (c) and −0.002 in panel (d)). The visual evidence in Fig. 3 is consistent
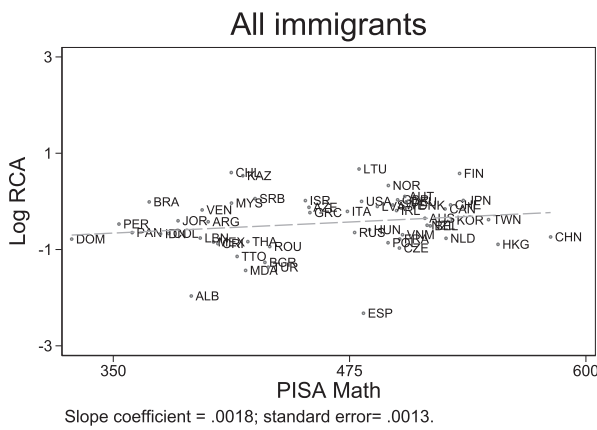
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[33] Because NOC codes pool construction workers, machine operators, and transportation workers in a single category (which are separate occupations in US data), we have 27 Canadian occupational categories.
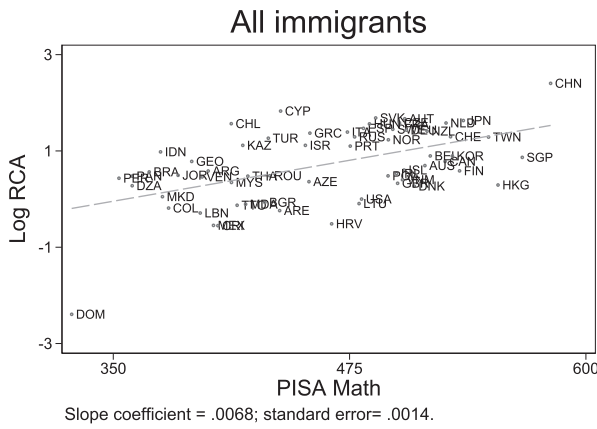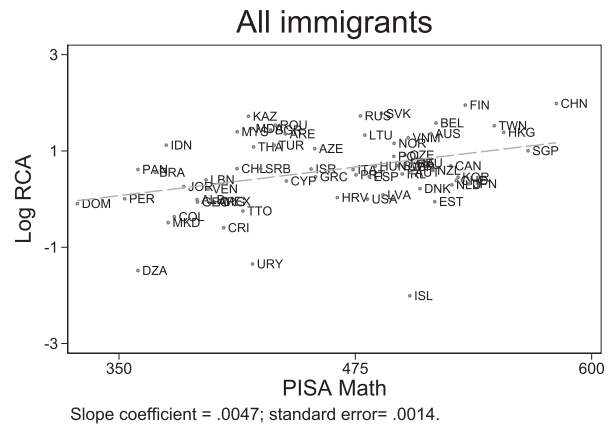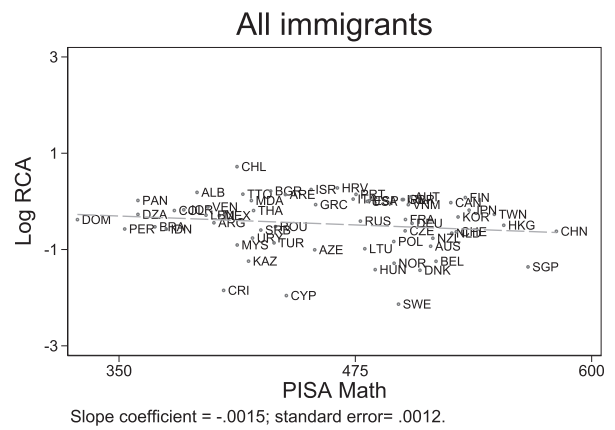
Fig. 3. Occupational specialization $\log\left(\frac{\Pi_{o|d}^{g}}{\Pi_{o|d}^{d}} \Big/ \frac{\Pi_{o'|d}^{g}}{\Pi_{o'|d}^{d}}\right)$ and PISA math score by immigrant origin-country, various occupations.

with foreign-born workers from countries whose educational institutions produce students who score highly on international assessments concentrating more strongly in jobs that require more abstract problem solving.

There is, however, a potential source of ambiguity in the results in Fig. 3. Because the population of foreign-born workers in the US combines individuals who were educated in their country of birth and individuals who migrated to the US at a young age and attended US schools, the evidence on the importance of being educated in the origin country for occupational specialization is not dispositive. To help resolve this ambiguity, in Fig. 4 we separate foreign-born workers into those who arrived in the US at age 18 or older (row one), and therefore were likely to have completed their K-12 education in their country of birth, and those who arrived in the US at age 17 or younger (row two), and therefore were likely to have completed part or all of their K-12 schooling in the US. Mathematicians and scientists appear in column one; computer software developers appear in column two. The evidence of comparative advantage in Fig. 3 is clearly driven by immigrants who arrived in the US at age 18 or older. For this group, we see a strong positive correlation between origin-country PISA scores and immigrant specialization in math and science and computer software (precisely estimated slope coefficients of 0.007 in panel (a) and 0.006 in panel (b)). For immigrants who arrived in the US at aged 17 or younger the correlations are much weaker (imprecisely estimated slope coefficients of 0.0003 in panel (c) and 0.001 in panel (d)).

The difference in specialization patterns among immigrants according to their age of arrival in the US is important because it helps neutralize a confounding force for occupational specialization. If some cultures accord higher status to individuals who perform well in school (e.g., Figlio et al., 2019; Hanushek and Kimko, 2000) or to individuals who take up specific occupations, irrespective of monetary compensation, then the correlation between country test scores and immigrant specialization patterns could reflect these cultural or social values, rather than the actual skills imparted by origin-country schools. The evidence in Fig. 4 is contrary to such a cultural values hypothesis.
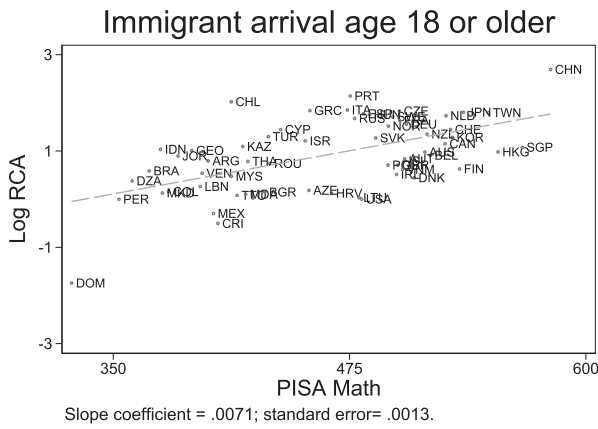
(a) Mathematicians and scientists
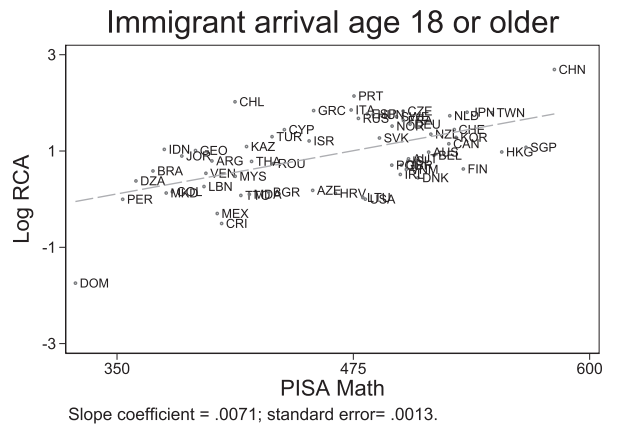
(b) Computer software developers
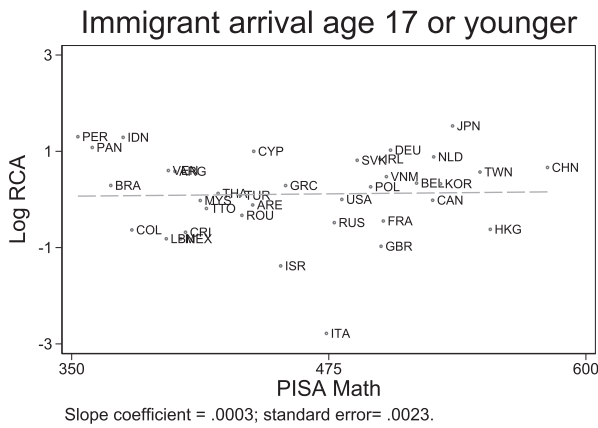
(c) Mathematicians and scientists

(d) Computer software developers

(e) Mathematicians and scientists

(f) Computer software developers

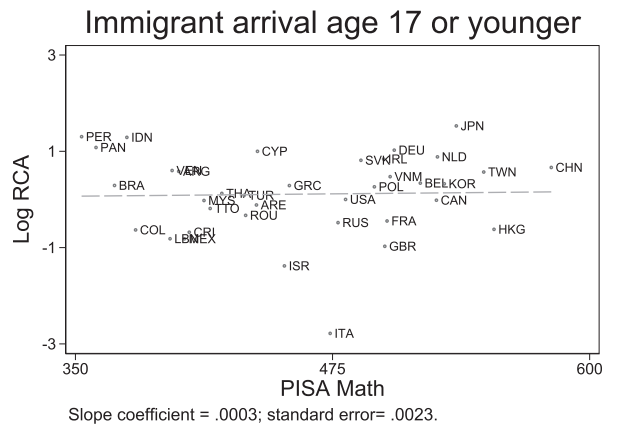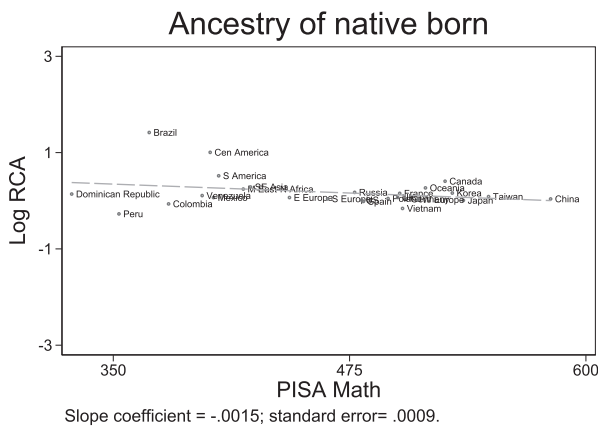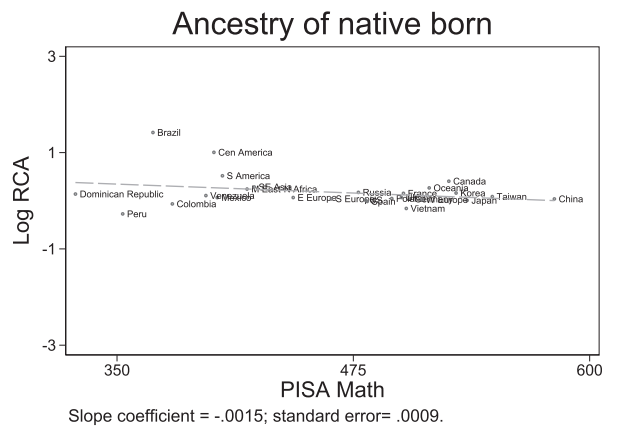**Fig. 4.** Occupational specialization $\left(\log, \frac{\Pi^s_{o|d}}{\Pi^d_{o|d}}, /, \frac{\Pi^s_{o'|d}}{\Pi^d_{o'|d}}\right)$ and PISA math score by immigrant origin-country, age of arrival in the US, and region of ancestry.

Table 2
OLS results for $\log \Pi_{old}^s$ (log share of hours worked) for US foreign-born Workers, using O*NET task intensities.

	(1) Average math	(2) 75ptl math	(3) 90ptl math
All foreign-born workers			
$PISA^s \times Y_{cog}^o$	4.711	4.062	6.323
	(2.237)	(1.774)	(1.837)
$PISA^s \times Y_{com}^o$	9.077	9.626	9.430
	(2.516)	(2.904)	(2.474)
$Ling^s \times Y_{cog}^o$	−0.179	−0.217	−0.143
	(0.420)	(0.387)	(0.401)
$Ling^s \times Y_{com}^o$	1.457	1.609	1.462
	(0.616)	(0.641)	(0.635)
Observations	1809	1597	1751
Adjusted R^2	0.402	0.415	0.401
Number of countries	69	61	67

Summary statistics for $\log \Pi_{old}^s$

Mean	Standard deviation	25ptl	75ptl
−3.6	0.98	−4.2	−2.9

Notes: This table reports selected OLS estimation results for Eq. (9). The sample covers 29 occupations and 61 to 69 origin countries. Hours worked are for male workers who are 25 to 54 years old, have at least four years of college education, earn positive wages, and do not reside in group quarters. Occupation and country of origin fixed effects are included in all regressions. Standard errors are clustered by origin country and reported in parentheses. See Appendix Table D.1 for complete regression results.

To evaluate social and cultural factors further, in row three of Fig. 4 we present results for US-born individuals categorized by their country or region of ancestry. If perceptions of social status are transmitted culturally, then the occupational choices of individuals may persist across generations and follow patterns associated with the origin countries of their elders (e.g., Figlio and Özek, 2020). In the ACS, ancestry is an individual's self-reported country of ancestry (e.g., the birth country of one's parents, grandparents, or great grandparents).[34] Since ancestry is sometimes identified as a geographic region instead of a country, we are forced to use more aggregate country groupings than in the previous analysis for foreign-born individuals. We have 25 to 28 ancestral regions (depending on the test-score measure used), which are comprised of 16 to 19 individual countries and eight aggregate regions.[35] In row three of Fig. 4, we see weak correlations (imprecisely estimated slope coefficients of 0.002 in panel (e), and 0.003 in panel (f)) between occupational specialization of individuals classified by their ancestral countries and PISA scores in these countries. These results are further evidence against cultural values explaining occupational specialization.

4. Empirical results

Our regression specification, based on Eq. (5), is for the log share of hours worked in occupation o by prime-age college-educated workers born in country s and residing destination country d (the US or Canada). It is given by,[36]

$$\log \Pi_{o|d}^s = \sum_{k \in \mathcal{C}} \left[\beta_{cog,k} PISA^s Y_k^o + \beta_{com,k} Ling^s Y_k^o + \beta_{dist,k} Dist^s Y_k^o \right] + \alpha_s + \alpha_o + \varepsilon_{d,o}^s. \tag{9}$$

We interact the country s PISA math score ($PISA^s$), linguistic proximity to the destination ($Ling^s$), and the log of geographic distance to the destination ($Dist^s$) with DOT or O*NET measures of occupational intensities in cognitive, communication, routine, and manual tasks (Y_j^o), where α_s is a fixed effect for country s (absorbing employment alternatives for country s workers and migration costs from s to the destination that are common across occupations) and α_o is a fixed effect for occupation o (absorbing the occupation wage per efficiency unit in the destination and occupational credentialing costs that are common across workers regardless of their nationality). We cluster standard errors by country of origin.

4.1. Occupational specialization in the US

4.1.1. Benchmark results

In Table 2, we present results using US data on occupational specialization and O*NET measures of task intensity, where we report results using DOT measures of task intensity in the appendix. We limit the reported coefficients estimates to those that

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[34] Our partition of ancestry groups is based the ACS variable (ANCESTR1), which records a respondent's first response for ancestry or ethnic origin.

[35] The individual countries are Brazil, Canada, China, Colombia, the Dominican Republic, France, Germany, Japan, Korea, Mexico, Peru, Poland, Russia, Spain, Taiwan, the US, Venezuela, and Vietnam; the aggregate regions are Central America and the Caribbean, Eastern Europe, the Middle East and North Africa, Oceania, South America, Southern Europe, Southeast Asia, and other Western Europe.

[36] βs differ from those in (3) by a common multiplier θ. We normalize $\theta = 1$ to simplify notation.

Table 3
Tests of positive sorting using O*NET task intensities.

	Sample: All immigrants		
	Test of (C′)		
Right-tail 5% Bootstrap Confidence interval	[2.11, 21.39]		
	Joint test of $\beta_{cog,cog} = \beta_{com,com} = \beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog} = 0$		
$\chi^2(3)$	35.1	P-value	0.00
	Sample: Immigrants arriving in US age 18 or older		
	Test of (C′)		
Right-tail 5% Bootstrap Confidence interval	[3.93, 31.79]		
	Joint Test of $\beta_{cog,cog} = \beta_{com,com} = \beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog} = 0$		
$\chi^2(3)$	35.7	P-value	0.00

Notes: When testing (C′), we test against the alternative hypothesis $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog} > 0$. When jointly testing (A′), (B′), and (C′), we test against the alternative hypothesis $\beta_{cog,cog} > 0$, $\beta_{com,com} > 0$, and $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog} > 0$. All results are based on regressions using the mean value of PISA scores from column 1 of Table 2.

allow us to evaluate positive worker sorting in cognitive and linguistic skills, as summarized in conditions (A′) to (C′). These results are for the interactions of PISA math scores (PISA^s) and linguistic proximity (Ling^s), which are standardized to take values between 0 and 1, with occupational intensities in cognitive and communication tasks. Results for our hypothesis tests on positive sorting are in Table 3; complete regression results appear in Appendix Table D.1. These baseline results are for men; appendix Table D.9 reports results for women.

In column (1), we measure PISA math scores using the average for a country, while in columns (2) and (3) we measure scores using the 75th and 90th percentiles. The choice of test-score moment determines the number of countries for which we have data. To evaluate sorting within the natural dimension of cognitive skill, consider the coefficient estimate for the interaction of the PISA math score and cognitive task intensity, which is positive and highly precisely estimated ($\hat{\beta}_{cog,cog} = 4.71$, standard error $= 2.24$). This interaction indicates that, consistent with Fig. 3, workers from countries that score more highly on international assessments specialize more strongly in occupations that are more intensive in cognitive reasoning. To interpret the coefficient estimate, compare countries at the 25th and 75th percentiles of PISA math scores internationally. The higher scoring country would have a 75% higher share (0.77 of a standard deviation) of its workers in the US employed in management and finance, the occupation at the 75th percentile of cognitive task intensity.[37]

Turning to linguistic skill, the positive and precisely estimated coefficient ($\hat{\beta}_{com,com} = 1.46$, standard error $= 0.616$) on the interaction of linguistic proximity and communication task intensity indicates that workers from countries that are more linguistically similar to the US concentrate more heavily in occupations that are more intensive in communication on the job. Comparing countries at the 25th and 75th percentiles of linguistic similarity to the US, the more similar country would have a 19% higher share (0.194 of a standard deviation) of its US-based workers employed in executive management, which is the occupation at the 75th percentile of communication intensity.[38] These first two sets of results are consistent with positive sorting of workers within the natural dimensions of skill.[39]

To evaluate results using other moments of the PISA test score distribution, Table 2 shows little change when we replace the average PISA score with the score at the 75th (column 2) or 90th (column 3) percentile. The similarity in results for alternative test-score moments suggests that the relevant difference in PISA scores for occupational sorting is the rightward or leftward shift of the score distribution for any individual country relative to other countries, rather than differences in score variance across countries. In Appendix Table D.3, we use DOT measures of occupational task intensity in place of O*NET measures. There is a positive and significant interaction between PISA math scores and DOT cognitive task intensity. With DOT measures of communication intensity (in place of O*NET measures of social skill intensity), the interaction with linguistic proximity to the US remains precisely estimated.

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[37] The value of 75% is calculated as $\left(\hat{\beta}_{cog,cog} \cdot Y^o_{cog} + \hat{\beta}_{cog,rou} \cdot Y^o_{rou} + \hat{\beta}_{cog,man} \cdot Y^o_{man} + \hat{\beta}_{cog,com} \cdot Y^o_{com}\right) \times \left(\text{PISA}^{75}_s - \text{PISA}^{25}_s\right)$, where PISA$^{75}_s$ and PISA$^{25}_s$ are the 25th and 75th percentiles of PISA scores, and O*NET task intensities are for the management and finance occupation.

[38] The value of 19% is calculated as $\left(\hat{\beta}_{com,cog} \cdot Y^o_{cog} + \hat{\beta}_{com,rou} \cdot Y^o_{rou} + \hat{\beta}_{com,man} \cdot Y^o_{man} + \hat{\beta}_{com,com} \cdot Y^o_{com}\right) \times \left(\text{Ling}^{75}_s - \text{Ling}^{25}_s\right)$, where Ling$^{75}_s$ and Ling$^{25}_s$ are the 25th and 75th percentiles of linguistic proximity, and the O*NET task intensities are for the executive management occupation.

[39] The OLS results in Table 2 omit observations for which country of birth-to-occupation matching is not observed in our 3% ACS sample. This omission may lead OLS results to underestimate true coefficient magnitudes if the missing countries have a weak comparative advantage in the occupations for which we observe no matching. In Appendix Table D.2, we re-estimate the regressions in Table 2 using Poisson pseudo maximum likelihood (PPML) (Silva and Tenreyro, 2006). The coefficient estimates are somewhat larger than in Table 2. Coefficient signs and patterns of significance are preserved, except for the linguistic proximity-communication intensity interaction, whose coefficient magnitudes are unchanged but whose standard errors are larger.

4.1.2. Sorting on multi-dimensional skill

To assess the strength of positive sorting for the two skill dimensions together, we test condition (C′), alone, and conditions (A′), (B′), and (C′), jointly, as shown in Table 3. Positive sorting in two dimensions requires that $\beta_{cog,cog}\beta_{com,com} - \beta_{com,cog}\beta_{cog,com} > 0$, or that the product of sorting within natural skill dimensions (the diagonal interaction terms) exceeds the product of sorting across natural skill dimensions (the off-diagonal interaction terms). We test the hypothesis using a bootstrap procedure to construct the empirical distribution of $\beta_{cog,cog}\beta_{com,com} - \beta_{com,cog}\beta_{cog,com}$. We draw 200 independent samples of immigrants to estimate this parameter. Values of $\beta_{cog,cog}\beta_{com,com} - \beta_{com,cog}\beta_{cog,com}$ are non-positive in just 9 of 200 instances. Table 3 reports the right-tail 5% confidence interval, where the lower bound is the 5th percentile of the 200 estimates and the upper bound is the maximum. We reject the hypothesis that (C′) is violated.

We use the same bootstrap procedure to test the joint hypothesis that (A′), (B′) and (C′) hold. Out of 200 samples, we find 9 instances where $\beta_{cog,cog}$, $\beta_{com,com}$, and $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog}$ are not simultaneously greater than zero, corresponding to a probability that at least one is false as $\frac{9}{200} = 0.045$ (i.e., we fail to reject the null at a 5% level of confidence). We also calculate the chi-square test statistic (see Appendix C for details) for the joint hypothesis that $\beta_{cog,cog} = \beta_{com,com} = \beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog} = 0$. Table 3 reports the test statistic and the p-value. We reject the null at any significance level. Overall, the evidence supports the positive sorting of workers across occupations in two dimensions of skill.

Evaluating other interaction terms, as shown in Appendix Table D.1, those that are precisely estimated are a negative coefficient for the PISA score-manual task intensity interaction (indicating, intuitively, that individuals from high-test-score countries are relatively unlikely to select into manual-intensive occupations) and a negative coefficient on the geographic distance-manual task intensive interaction (indicating that workers from countries closer to the US are more likely to select into manual jobs). These results appear to be driven by differences between countries in Latin America and countries in other origin regions for US immigration. Latin America has among the lowest PISA scores for countries in our sample and comprises the countries (other than Canada) that are physically closest to the US, thereby allowing for more undocumented and low-skilled immigration (Grogger and Hanson, 2011). It thus appears that migrants from nearby countries with relative weak cognitive training are disproportionately likely to work in manual occupations.

4.1.3. Interpreting the results

To aide in interpreting the results more fully, we calculate for each occupation the implied marginal change in occupational sorting (as measured by $\Delta \log \Pi_{old}^{s}$) in response to a one standard deviation change in the PISA math score or linguistic proximity to the US. The coefficients we use for PISA math scores are $\hat{\beta}_{cog,cog}$, $\hat{\beta}_{cog,man}$, and $\hat{\beta}_{cog,com}$, which correspond to the interaction terms $PISA^{s} \times Y_{cog}^{o}$ (PISA score-cognitive task intensity), $PISA^{s} \times Y_{man}^{o}$ (PISA score-manual task intensity), and $PISA^{s} \times Y_{com}^{o}$ (PISA score-social task intensity) respectively. For linguistic proximity, we use the coefficients $Ling^{s} \times Y_{com}^{o}$ (linguistic proximity-social task intensity). We limit the calculations to these coefficients because they are the ones with precisely estimated interactions between task intensities and PISA scores or linguistic proximity. All coefficients are from column (1) of Appendix Table D.1.

Table 4 reports the marginal changes in $\log \Pi_{old}^{s}$ for the five most positively and five most negatively affected occupations. Given the presence of occupation fixed effects in the underlying regression, these marginal changes are only meaningful with respect to some base occupation, which we select to be administrative managers given its place in the middle of occupations in terms of cognitive and communication task intensities (see Appendix Table B.2). The values in parentheses are bootstrapped standard errors, calculated by drawing 200 independent samples (where bootstrapped samples are drawn from clustered country-occupation pairs). We estimate (9) for each sample, which provides 200 estimates of $\left(\hat{\beta}_{cog,cog} \times Y_{cog}^{o} + \hat{\beta}_{cog,man} \times Y_{man}^{o} + \hat{\beta}_{cog,com} \times Y_{com}^{o} \right) \times Std(PISA^{s})$, where $Std(PISA^{s})$ is the standard deviation of PISA math score, and which we evaluate relative to the administrative manager occupation. We calculate impacts for the increase in linguistic proximity analogously.

Intuitively, an increase in the PISA math score increases the probability of working in cognitive-task-intensive occupations, while reducing the likelihood of employment in manual-task-intensive occupations. Relative employment shares increase by 11.9 log points for management and finance and 11.1 log points for executive management, while they decline by 41.8 log points for low-skill service workers and 40.3 log points for transportation workers. An increase in linguistic proximity raises relative employment shares among other managers by 2.7 log points and executive management by 2.2 log points—two occupations that are intensive in communication in English—while reducing employment shares among machine operators and transportation workers by 25.1 and 21.4 log points, respectively. Three manual occupations—transportation, machine operation, and mechanics and repairers—are among the largest relative employment declines in response to either shock.

4.2. Occupational specialization in Canada

Our results for the US are consistent with comparative advantage by origin country playing a significant role in the occupational choice of immigrant workers in the US. We see clear evidence of positive sorting in the dimensions of cognitive and linguistic skills. Because the US immigration system is based on a complex set of preferences that govern which types of individuals are admitted, we cannot be sure that our results are not somehow the byproduct of differential national selection built into US visa policies. To help isolate the role of comparative advantage in immigrant sorting, we present results parallel to those in Section 4.1

Table 4

Changes in $\log \Pi^s_{old}$ in response to one-standard-deviation increase in PISA math score and linguistic proximity to the US (relative to the administrative manager occupation).

Panel I: One standard deviation increase in PISA math score			
Occupations with the largest increase in $\log \Pi^s_{old}$		Occupations with the largest decrease in $\log \Pi^s_{old}$	
Manager, Finance	0.119 (0.033)	Clerical, Medium-skill	−0.329 (0.046)
Managers, Chief Executive	0.113 (0.015)	Machine operators	−0.344 (0.065)
Accountants	0.070 (0.047)	Mechanics & repairers	−0.355 (0.054)
Engineers	0.058 (0.043)	Transportation workers	−0.408 (0.059)
Scientists, mathematicians	0.010 (0.046)	Service, low-skill	−0.424 (0.054)
Panel II: One standard deviation increase in linguistic proximity to US			
Occupations with the largest increase in $\log \Pi^s_{old}$		Occupations with the largest decrease in $\log \Pi^s_{old}$	
Manager, others	0.028 (0.009)	Clerical, low-skill	−0.165 (0.055)
Managers, Chief Executive	0.023 (0.007)	Computer software developer	−0.175 (0.058)
Salespersons	0.006 (0.002)	Mechanics & repairers	−0.211 (0.069)
Lawyers	−0.004 (0.001)	Transportation workers	−0.221 (0.073)
Managers, Finance	−0.009 (0.003)	Machine operators	−0.261 (0.086)

Notes: The marginal changes are calculated using the expressions $\left(\hat{\beta}_{cog,cog} \times Y^o_{cog} + \hat{\beta}_{cog,man} \times Y^o_{man} + \hat{\beta}_{cog,com} \times Y^o_{com}\right) \times Std(PISA^s)$ in Panel A, and $\left(\hat{\beta}_{com,com} \times Y^o_{com}\right) \times Std(Ling^s)$ in Panel B, where $Std(PISA^s)$ and $Std(Ling^s)$ are, respectively, the standard deviations of PISA math score and linguistic proximity. The standard errors in parentheses are estimated from 200 independent bootstrapped samples drawn from clustered country-occupation pairs.

for immigrants in Canada, in which immigrants with greater human capital are more likely to attain an entry visa. Whereas the US system reserves the large majority of visas for relatives of US residents, Canada instead favors immigrants who score highly on the country's point system, which rewards education, labor-market experience, language ability, entrepreneurship, and youth. Comparing results in US and Canadian data allows us to see whether, despite differences in visa policies, there are similar patterns of revealed comparative advantage in occupational selection by immigrant source country.

Table 5 reports our results for Canada (again for foreign-born males who are 25 to 54 years old, have a college education or higher degree, and earn positive wages).[40] Because in some cases the Canadian Census reports the origin for immigrants at the region rather than country level, our data span 22 origin regions.[41] The positive and precisely estimated coefficient for the interaction of the PISA math score and cognitive task intensity ($\hat{\beta}_{cog,cog} = 3.7$, standard error $= 1.72$) indicates that in Canada, as in the US, workers from regions that score more highly on international assessments specialize more strongly in occupations that are more intensive in cognitive tasks. Comparing regions at the 25th and 75th percentiles of PISA math scores, the higher scoring region would have a 72% higher share (0.91 of a standard deviation) of its workers in Canada employed in management and finance (the occupation at the 75th percentile of cognitive task intensity). These impacts are modestly smaller than those for the US. For Canada, as for US, the interaction of linguistic proximity and communication task intensity is positive and precisely estimated ($\hat{\beta}_{com,com} = 2.90$, standard error $= 0.69$).

When using the Canadian sample to test the violation of hypothesis (A′), we find non-positive values of $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog}$ in 19 of 200 instances, corresponding to a probability of $\frac{19}{200} = 0.095$ that (C′) is false. When jointly testing hypothesis (A′), (B′) and (C′), we find that 30 out of 200 instances where $\beta_{cog,cog}$, $\beta_{com,com}$, and $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog}$ are not simultaneously greater than zero, corresponding to a probability of $\frac{30}{200} = 0.15$ that at least one is false. These results are supportive of positive sorting of workers in multi-dimensional skill, although we obtain less precision in Canadian data than in US data. Lower precision may be partly the result of how the Canadian Census aggregates source countries into regions—i.e., we have 22 source regions for Canada in Table 5 versus 69 source countries for the US in Table 1—which may compress variation in the Canadian data.

4.3. Separating immigrants by age of arrival in the US

Next, we group immigrants by their age of arrival in the US, which separates them based on where their K-12 education occurred. Doing so isolates the importance of being exposed to educational institutions in an immigrant's birth country, as opposed to being exposed to birth-country cultural values only, by virtue of having parents from a given origin. We focus on results using average PISA scores; results using other moments are very similar. These baseline results are again for men; appendix Table D.10 reports results for women.

In panel I of Table 6, we limit the sample to immigrants who arrived in the US at age 18 or older and therefore completed their K-12 education abroad. Signs and significance of coefficient estimates are identical to those in Table 2 and remain consistent

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[40] Appendix Table 13 reports the complete regression results.
[41] The data include 16 individual countries (Australia, Brazil, Canada, China, Colombia, England, France, Germany, Hong Kong, Italy, Korea, Mexico, Russia, Poland, Romania, and the US), and six aggregate regions (Central America, Eastern Europe, the Middle East, South America, Southeast Asia, other Western Europe).

Table 5

OLS regression results for $\log \Pi_{old}^{s}$, Canadian immigrants, using O*NET task intensities.

	(1) Average math	(2) 75ptl math	(3) 90ptl math
$PISA^{s} \times Y_{cog}^{o}$	3.749	3.312	3.380
	(1.720)	(1.609)	(1.625)
$PISA^{s} \times Y_{com}^{o}$	7.292	7.311	7.511
	(4.206)	(4.001)	(4.150)
$Ling^{s} \times Y_{cog}^{o}$	0.00891	0.00510	−0.00937
	(0.354)	(0.353)	(0.354)
$Ling^{s} \times Y_{com}^{o}$	2.909	2.886	2.852
	(0.696)	(0.708)	(0.722)
Observations	555	555	555
Adjusted R^{2}	0.684	0.685	0.685
Number of countries	22	22	22

Summary statistics for $\log \Pi_{old}^{s}$

Mean	Standard deviation	25ptl	75ptl
−3.5	0.79	−4.0	−2.9

Notes: Regression units are 27 occupations × 22 aggregate regions. The sample is restricted to workers who are male and 25 to 54 years old, have a college education or above, and earn positive wages. Occupation and region-specific fixed effects are included in all regressions. Standard errors are clustered at the region level and reported in parentheses.

Table 6

OLS results for $\log \Pi_{old}^{s}$, by immigrant age of arrival and native-born ancestry, using ONET task intensities.

	(1) Average math	(2) 75ptl math	(3) 90ptl math
Panel I: Immigrants arriving at age 18+			
$PISA^{s} \times Y_{cog}^{o}$	5.250	5.238	7.329
	(2.725)	(2.213)	(2.160)
$PISA^{s} \times Y_{com}^{o}$	9.948	9.708	9.934
	(2.860)	(3.085)	(2.906)
$Ling^{s} \times Y_{cog}^{o}$	−0.508	−0.515	−0.507
	(0.533)	(0.498)	(0.508)
$Ling^{s} \times Y_{com}^{o}$	1.820	1.956	1.882
	(0.771)	(0.803)	(0.790)
Observations	1691	1496	1633
Adjusted R^{2}	0.395	0.400	0.393
Number of countries	69	61	67
Panel II: Immigrants arriving before age 18			
$PISA^{s} \times Y_{cog}^{o}$	−0.107	0.522	1.376
	(2.187)	(1.863)	(1.874)
$PISA^{s} \times Y_{com}^{o}$	3.960	5.283	5.208
	(2.680)	(2.390)	(2.367)
$Ling^{s} \times Y_{cog}^{o}$	−0.411	−0.467	−0.386
	(0.500)	(0.490)	(0.506)
$Ling^{s} \times Y_{com}^{o}$	1.350	1.585	1.415
	(0.700)	(0.698)	(0.698)
Observations	1350	1193	1294
Adjusted R^{2}	0.389	0.391	0.392
Number of countries	68	60	66
Panel III: Native born by region of ancestry			
$PISA^{s} \times Y_{cog}^{o}$	1.279	3.029	1.781
	(2.011)	(1.623)	(1.912)
$PISA^{s} \times Y_{com}^{o}$	2.907	2.811	5.493
	(3.099)	(2.622)	(2.980)
$Ling^{s} \times Y_{cog}^{o}$	−0.473	−0.422	−0.568
	(0.250)	(0.177)	(0.245)
$Ling^{s} \times Y_{com}^{o}$	−1.016	−1.116	−1.003
	(0.732)	(0.640)	(0.682)
Observations	795	714	743
Adjusted R^{2}	0.532	0.583	0.563
Number of countries	28	25	26

Notes: Standard errors are clustered by origin country and reported in parentheses. The full set of regressors is the same as for the regressions reported in Table 2.

with positive sorting. The magnitudes of coefficient estimates are now larger, suggesting that positive sorting is stronger. Comparing 25th and 75th percentile countries for PISA math scores, the higher scoring country would have a 86.2% higher share (0.88 of a standard deviation) of its workers in management and finance (the 75th percentile occupation for cognitive task intensity); comparing 25th and 75th percentile countries for linguistic similarity to the US, the more similar country would have a 24.2% higher share (0.25 of a standard deviation) of its workers in executive management (at the 75th percentile for communication intensity).

In evaluating hypothesis (C′), Panel B of Table 3 shows that the right-tail 5% confidence interval does not contain zero. When we replicate the bootstrap procedure on samples with immigrants arriving in the US at age 18 or older, we find non-positive values of $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog}$ in just 1 of 200 instances. These results reject a violation of (C′). When we test the joint hypothesis (A′), (B′) and (C′), we find 1 out of 200 instances where $\beta_{cog,cog}$, $\beta_{com,com}$, and $\beta_{cog,cog}\beta_{com,com} - \beta_{cog,com}\beta_{com,cog}$ are simultaneously greater than zero. We also find a large chi-square test static, rejecting the null at any significance level.

In panel II of Table 6, we examine immigrants who arrived in the US at age 17 or younger. These individuals likely migrated at the behest of their parents or another family member. Since they arrived in the US before age 18, they would have completed at least part of their K-12 education in the US. For this group, the coefficient on the PISA math score and cognitive task intensity interaction is small and highly imprecisely estimated ($\hat{\beta}_{cog,cog} = -0.11$, standard error = 2.2). When foreign-born workers undertake K-12 education outside of their country of origin, there is no longer a connection between cognitive skill (as measured by international assessments) and worker sorting across occupations in the US. The results are consistent with the quality of educational institutions in origin countries (rather than origin-country cultural values) playing a determinative role in occupational choice by their workers abroad.

Panel II of Table 6 reveals a positive effect ($\hat{\beta}_{com,com} = 1.35$, standard error = 0.7) for the interaction of linguistic proximity to the US and communication task intensity. Similar to immigrants who arrived as adults, linguistic proximity to the US affects occupational sorting for immigrants who arrived as children. Those from countries with weaker facility in English are less likely to select more communication-intensive jobs. Bleakley and Chin (2004) find that among US immigrants from non-English-speaking countries, those arriving before age 14 tend to have stronger fluency in English than those arriving at age 14 or later. They attribute this result to changes in brain function at puberty, which occur around age 14 and diminish the ability to learn new languages. Motivated by their findings, in Appendix Table D.5 we restrict the sample of immigrants to those who arrived in the US at age 13 or younger. We continue to find a small and insignificant interaction between PISA scores and cognitive task intensity ($\hat{\beta}_{cog,cog} = 2.5$, standard error = 2.86). The interaction between linguistic proximity to the US and communication intensity becomes smaller and statistically insignificant ($\hat{\beta}_{com,com} = 0.74$, standard error = 1.056). Intuitively, immigrants arriving in the US as young children are less affected by English-language proficiency in their birth countries.

In panel III of Table 6, we examine US-born individuals by their region of ancestry. Comparing results with panel I, the interaction between PISA math scores in the ancestral region and cognitive task intensity is approximately one third the magnitude; it is imprecisely estimated for average PISA scores and precisely estimated for 75th and 90th percentile scores. The interaction between linguistic proximity to the US and communication task intensity is now negative, in contrast to the panel I results. Summarizing results across panels in Table 6, evidence of positive sorting according to cognitive and linguistic skills of the origin country is much stronger for immigrants who arrive as adults than for immigrants who arrived as children or whose parents or older generations where those who migrated to the US.

In Appendix Table D.6, we replicate the results in Table 6, now using DOT task intensities in place of O*NET task intensities. For immigrants arriving at age 18 or older, shown in panel I, we again find positive and statistically significant interactions between PISA test scores and cognitive task intensity and between linguistic proximity and communication task intensity. Similar to the above, neither result holds for immigrants arriving before age 18 (panel II) or native-born individuals identified by their region of ancestry (panel III).

4.4. Extended results

4.4.1. Temporary immigration

In a further exercise, we examine the importance of time spent in the US for immigrant sorting across occupations. One reason tenure in the US may matter has to do with rules governing the temporary immigration of skilled workers. In the years up to and including our sample period, the US authorized 65,000 to 85,000 H-1B visas per year to foreign-born workers in specialty occupations. The visas allow a recipient to remain in the US for three years with one three-year extension.[42] In practice, the majority of these visas go to workers in computing and engineering occupations who are employed by major technology companies (Bound et al., 2015, 2017). The role of H—1B visas in tracking foreign-born workers into technology-related jobs could imply that visa allocation and work rules are distorting occupational sorting and thereby diminishing the effect of comparative advantage.

Given that the maximum duration of stay for workers on H—1B visas is six years, we re-run our analysis for immigrants who have been in the US for 7 years or more. The results, in Appendix Table D.7 for all immigrants and Appendix Table D.8 for

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[42] This implies that that the number of individuals in the US on H—1B visas an any moment in time should not exceed 510,000. Because the US government does not track the location of H—1B visa holders, there is no official count of the stock of US workers who hold H—1B visas.

immigrants who arrived in the US at age 18 or older, are very similar to those already reported. We interpret these findings to mean that temporary work visas are unlikely to be a significant confound.

4.4.2. Occupational downgrading

A second reason that tenure in the US may be related to job choice is the phenomenon of occupational downgrading among recent arrivals in a new labor market (Dustmann et al., 2013). If immigrants' origin-country training or work experience do not match the specific needs of US employers or meet US occupational licensing requirements, it may take new immigrants time to work their way into a job that is commensurate with their skills. In the case of Russian Jews migrating to Israel following the dissolution of the Soviet Union—a population in which the majority of individuals had some post-secondary education—Eckstein and Weiss (2004) report substantial occupational downgrading in the years immediately after arrival followed by steady occupational upgrading over the ensuing decade. The results in Appendix Tables D.7 and D.8, for the sample of immigrants that have at least six years of tenure in the US, suggest that whatever temporary occupational downgrading takes place is unlikely to negate the role of comparative advantage in sorting across jobs.

Nevertheless, the question remains whether college-educated immigrants are subject to occupational downgrading of some kind. Evaluating downgrading is complicated by the fact that the ACS does not report an immigrant's occupation prior to coming to the US. However, it does report the first and second university degree fields for individuals who completed four years of college or an advanced degree. This allows us to evaluate the matching of degree holders to occupations for the subset of degree fields that track individuals into specific lines of work. Among immigrants in our sample, the most common degree fields in descending order of importance are engineering, business, computer and information sciences, social sciences, physical sciences, and biology and life sciences, which together account for 67.3% of primary degrees held by immigrants in our sample. Whereas engineering and computer information systems map to specific jobs, business and social sciences do not. Biological and physical sciences would appear to be somewhere in between.

We evaluate occupational matching for immigrants whose primary or secondary degree fields belong to the narrower category of computer-engineering (which includes degrees in computer information systems, computer science, and engineering),[43] and the broader category of STEM (which includes computer-engineering plus mathematics and biological and physical sciences).[44] We examine whether origin-country PISA scores or linguistic similarity to the US affect the likelihood that individuals who majored in these fields take degree-appropriate jobs. We match computer-engineering degrees with jobs in three occupations: computer software developers, computer system analysts, and engineers; we match STEM degrees to these three occupations plus mathematicians and scientists. Evaluating matching has meaning only relative to some base occupation, which we select to be less-skilled occupations for which no college degree would seem to be required: construction, transportation, machine operation, mechanics and repairers, low-skill services, and mid-skill services. In Table 4, we see that employment in these occupations is relatively low in countries with high PISA scores and greater linguistic proximity to the US. The regression specification is,

$$\log \Pi^s_{o|d} - \log \Pi^s_{o'|d} = \alpha + \beta \text{PISA}^s + \gamma \text{Ling}^s + \phi \text{Dist}^s + \varepsilon_s, \tag{10}$$

where $\log \Pi^s_{o|d} - \log \Pi^s_{o'|d}$ is the log employment share in computer-engineering or STEM occupations, indexed by o, relative to the log employment share for the aggregate of low-skill occupations, indexed by o', for the sample of foreign-born workers whose primary or secondary degree corresponds to occupation o.[45] We report results for all immigrants, those who arrived in the US at age 18 or older, and older arrivals with at least 7 years in the US.

Appendix Table D.11 reports estimation results for (10). We begin with all immigrants in panel I. In column (1), we see that computer-engineering degree holders from higher PISA score countries are more likely to be employed in computer-engineering occupations (than in low-skilled occupations) when compared to computer-engineering degree holders from lower PISA score countries ($\hat{\beta} = 8.25$, t-value = 1.95). Similar results obtain for the broader STEM occupational/degree category in column (2). These findings are consistent with two interpretations. One is relative occupational downgrading (individuals from high PISA score countries are more likely to work in occupations that utilize their computer-engineering or STEM training) and another is occupational comparative advantage (individuals from high PISA score countries are more likely to work in cognitive-task-intensive occupations).

To distinguish between these explanations, in column (3) we compare employment in high-skill, non-STEM occupations to employment low-skill occupations, for individuals whose primary or secondary university degree is in a STEM field. If occupational downgrading accounts for the results in the first two columns of Appendix Table D.11, then we should find much smaller impacts of PISA scores on selection into high-skill, non-STEM occupations (since STEM degrees are not essential for these jobs). Coefficient estimates are very similar in columns (1), (2), and (3), which indicates that individuals from high PISA score countries

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[43] These titles correspond to ACS general degree fields, which contain the following detailed degree fields: computer programming, computer science, information science, computer information management, and computer networking; all engineering fields; and mathematics and computer science.

[44] The additional detailed degree fields in the STEM category include: mathematics, applied mathematics, and statistics and decision science; biology, biochemical sciences, botany, molecular biology, ecology, genetics, zoology, neuroscience, and cognitive science; and astronomy, astrophysics, atmospheric sciences, chemistry, geology, geosciences, oceanography, physics, and materials science.

[45] Because we are comparing single pairs of occupations across workers grouped by origin country, we cannot include origin-country or occupation fixed effects in the regression. Differences in task intensities between the two occupations are absorbed into the regression coefficients.

Table 7
OLS results for $\log \Pi^s_{old}$ with additional controls.

	(1)	(2)	(3)	(4)	(5)
Panel I: Estimated Coefficients					
$PISA^s \times Y^o_{cog}$	4.711	5.054	3.544	5.385	3.904
	(2.237)	(2.443)	(2.746)	(2.291)	(2.725)
$PISA^s \times Y^o_{rou}$	−1.009	−0.904	−1.237	−1.116	−0.936
	(1.503)	(1.810)	(1.789)	(1.612)	(1.958)
$PISA^s \times Y^o_{man}$	−6.763	−5.211	−6.471	−6.734	−5.652
	(1.959)	(2.190)	(2.792)	(2.075)	(2.883)
$PISA^s \times Y^o_{com}$	9.077	7.336	3.869	6.891	3.020
	(2.516)	(2.960)	(3.239)	(2.832)	(3.562)
$Ling^s \times Y^o_{cog}$	−0.179	−0.205	−0.395	−0.0556	−0.300
	(0.420)	(0.425)	(0.478)	(0.467)	(0.487)
$Ling^s \times Y^o_{rou}$	−0.0547	0.0202	0.0196	−0.0890	−0.0221
	(0.389)	(0.401)	(0.423)	(0.432)	(0.451)
$Ling^s \times Y^o_{man}$	−0.326	−0.269	−0.342	−0.323	−0.367
	(0.460)	(0.471)	(0.536)	(0.525)	(0.548)
$Ling^s \times Y^o_{com}$	1.457	1.313	0.898	1.033	0.838
	(0.616)	(0.599)	(0.591)	(0.619)	(0.575)
$Dist \times ONET$	✓	✓	✓	✓	✓
$Tertiary \times ONET$		✓			✓
$Findev \times ONET$			✓		✓
$Econfreedom \times ONET$				✓	✓
N	1809	1684	1715	1809	1643
Panel II: Tests of positive sorting					
			Test of (C′)		
The probability that (C′) is rejected	0.02	0.03	0.04	0.09	0.06
			Test of (A′) (B′) (C′)		
The probability that at least one is rejected	0.02	0.03	0.06	0.09	0.085

Notes: This table reports results for the specification in column (1) of Table 2 plus interactions between the four occupational task intensities and the following variables: Tertiary, the share of the adult population with tertiary education completed; Findev, the share of private credit to the private sector in GDP; and Econ Freedom, the Fraser Institute's Economic Freedom Index. Standard errors are clustered by origin country and reported in parentheses.

(with university degrees in STEM fields) are relatively likely to select into high-skill jobs, be they in STEM or non-STEM occupations. A similar pattern holds for immigrants arriving in the US at age 18 or older, in panel II, and for these older immigrants with at least seven years in the US, in panel III. We interpret these results as confirming our earlier findings on comparative advantage and as unsupportive of relative occupational downgrading (in this particular and narrow application of the concept).

4.4.3. Robustness to additional controls

Thus far, our regression specification has included interactions between occupational task intensities and country supplies of skills related to these intensities. Other country characteristics may also shape comparative advantage. Literature on the gravity model in international trade, from which we draw inspiration for our estimation approach, considers many such factors in the context of industrial (rather than occupational) comparative advantage, including supplies of human and physical capital (Romalis, 2004; Costinot, 2009), quality of legal and other institutions (Anderson and Marcouiller, 2002; Levchenko, 2007; Nunn, 2007; Nunn and Trefler, 2014), and depth of financial markets (Chor, 2010). To evaluate the robustness of our results to controlling for sources of industrial comparative advantage known to matter in a trade context, we expand our specification to include interactions between occupational task intensities and additional country characteristics.

Core determinants of comparative advantage in trade include supplies of human and physical capital. To capture human capital, we include the share of the population age 15 and older with tertiary education completed (from Barro and Lee (2013), averaged over 2000 to 2010, available for all countries in our data). To capture access to capital, we include a commonly used measure of financial development (Rajan and Zingales, 1998; Beck et al., 2000), the share of private credit to the private sector in GDP (from World Development Indicators, averaged over 2000 to 2015, available for 65 of our sample countries). To measure the quality of institutions, we use the Economic Freedom Index from the Fraser Institute, which averages over sub-indices for the strength of property rights, government regulation, trade restrictions, and the size and quality of government (for 2010, available for all sample countries). As discussed in Francois and Manchin (2013), this index is more expansive than rule of law measures based on Kaufmann et al. (2005), which were used in much of the initial empirical work on institutions and trade (e.g., Levchenko, 2007).

In Table 7.I, we see that adding interactions between occupational factor intensities and other country characteristics leads to larger estimates of the interaction between PISA scores and cognitive task intensity (except for the case of financial development

in columns 3 and 5) and either modestly larger or smaller estimates of the interaction between linguistic similarity to the US and communication task intensity. See Appendix Table D.12 for the full set of regression coefficient on the added interaction terms.

To test the strength of positive sorting, we draw 200 independent samples of immigrants to estimate each specification. In testing (C′), we find the numbers of incidences where $\beta_{cog,cog}\beta_{com,com} - \beta_{com,cog}\beta_{cog,com}$ are non-positive are 4, 6, 8, 18, and 12, respectively, which imply that the probability that reject the null is no larger than 9% for all cases (See Table 7.II). In jointly testing (A′), (B′), and (C′), we find the probability of rejecting the null is also no larger than 9%.[46]

5. Conclusion

Observers have long noticed that upon arriving in a new country, immigrants often congregate in occupations according to their country of origin. The standard explanation for such occupational clustering is the presence of migration networks. Early arrivals from a given origin country just happen to choose one set of jobs over another, and, because job search is costly for new arrivals and information flows relatively freely within origin-country migrant communities, later cohorts of immigrants tend to follow in the footsteps of the pioneers. No doubt, migration networks have been a powerful force in immigrant job choice in many historical episodes. Yet, such networks provide a less compelling explanation for job search among the highly educated. Individuals choose to become computer programmers not because it seems like the obvious thing to do but because their training and aptitude makes such a difficult career choice feasible. In jobs in which cognitive reasoning and analytical skill are required, the quality of educational institutions in a country likely affect the career opportunities that individuals from the country have when choosing to work abroad.

We present evidence consistent with national comparative advantage in immigrant job choice and with positive sorting in multidimensional skill across jobs. US immigrants from countries whose students score more highly on international assessments—as indicative of the quality of educational institutions in the origin country—specialize more strongly in jobs that are more intensive in cognitive skill. Similarly, US immigrants from countries that are more linguistically similar to the US are more concentrated in jobs that are intensive in interpersonal communication. One implication of these patterns is that changes in the origin-country-bias of US immigration policy—whether implicit or explicit—would change the relative supply of labor across occupations and therefore US employment in these occupations. In effect, the US can choose its occupational comparative advantage by changing how it allocates immigration visas across countries of origin of migrants (at least among those who arrive as adults). Favoring countries that achieve higher test scores in awarding visas is one path to this outcome. Introducing an explicit point system for immigrant admissions, as in Canada, is another path. As the US ponders comprehensive reform to its immigration policies, its comparative advantage across occupations would appear to be in play.

Data availability

Immigration and Occupational Comparative Advantage (Original data) (Mendeley Data)

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[46] Note that, in Panel I, because the standard errors are clustered at the group-level, the statistical significance in Panel I are not necessarily consistent with the *p*-value estimated using the bootstrap sample.

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