The Occupations and Human Capital of U.S. Immigrants*

Todd Schoellman †

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Abstract

This paper uses the principle of comparative advantage in labor markets to estimate the multi-dimensional human capital endowments of immigrants by characterizing the skill utilization of their chosen occupations. This approach allows for estimation of physical skill and cognitive ability endowments, which are difficult to measure directly. Estimation implies that immigrants as a whole are abundant in cognitive ability and scarce in experience/training and communication skills. They are not estimated to be abundant or scarce in education. The simulated wage impact of immigration is skewed: the largest loss from immigration is 2.8% lower wages, but the largest gain is 0.3% higher wages. The fraction of an occupation's labor force that is foreign-born explains little of the wage effects; the bulk is explained by the occupation's skill utilization.

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†Address: John E. Walker Department of Economics, Clemson University, Clemson, SC 29634. E-mail: todd.schoellman@gmail.com.

1 Introduction

After reaching an historic low in 1970, the immigrant share of the U.S. population has risen steadily. Today there are four times as many immigrants as 1970, comprising 12.6% of the population.[1] The rise in the number of immigrants has led to renewed interest in their effects on the labor market outcomes for native workers.

Most recent research focuses on the skills of immigrants. If workers with different skill sets are imperfect substitutes in production and immigration changes the aggregate supply of workers with different skill sets, then immigration affects the relative wages of native workers.[2] To apply this approach, it is necessary to specify correctly the relevant skill sets. Papers in the literature have mostly used various Census and CPS questions to measure immigrants' skills, including some combination of education, experience, field of study, occupation, and language skills. Although promising, this literature is limited along two dimensions. First, responses to these questions imperfectly measure true skills. For example, the U.S. labor market value of a year of foreign schooling varies widely depending on the immigrant's birth country, suggesting differences in the quality of a year of schooling from different countries (Schoellman 2009). Second, there are no questions to identify important and potentially relevant components of human capital such as cognitive ability.

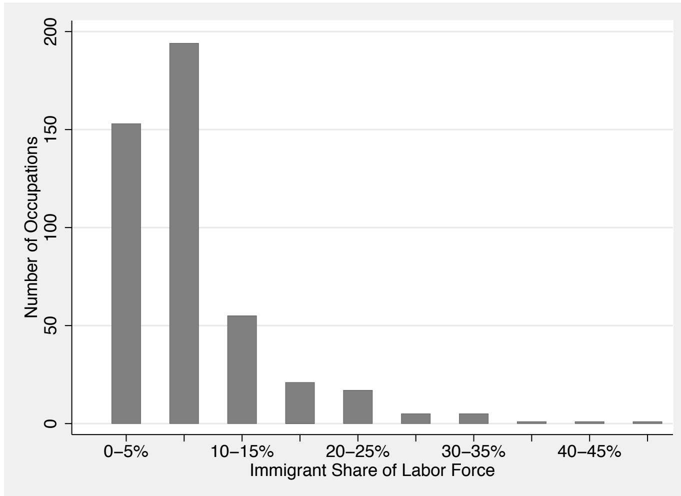
This paper contributes to the existing literature along both dimensions by estimating immigrants' skills using their observed occupational choices. An individual's occupation reveals a great deal of information about their likely skills: their education, cognitive ability, physical strength, and so on. It is possible to quantify this information by observing the occupational choices of many immigrants from a single country. The primary advantage of inferring skills is that I can estimate endowments of skills that are measured imperfectly or not at all. For example, while the Census lacks a question that measures immigrants' cognitive ability, I can infer it by observing whether immigrants are more likely than natives to be physicists or engineers. This approach could be useful in a variety of contexts, but it is particularly applicable to immigration given how widely immigrants' occupational choices diverge from those of natives, shown in the histogram in Figure 1. Foreign-born workers who immigrated as adults are 8.6% of this paper's sample, but the fraction in a given Census occupation ranges from 0.6% to 46%.

To quantify the information available in occupational choices, I use a model of labor

[1]Migration Policy Institute (2009), using Census and ACS data.

[2]Borjas (1999) calls this the factor proportions approach, to distinguish it from the earlier spatial correlation approach that used cross-sectional (state or city) variation in immigration to estimate the wage impact of immigration; see his survey for more details.

Figure 1: Distribution of Occupations by Immigrant Share of Labor Force



Note: Immigrants are 8.6% of the sample for this paper.
There are 453 Census occupations used in the analysis.

markets similar to Lazear (2009). Human capital is a vector of different attributes such as physical skills, education, or cognitive ability. Workers have heterogeneous endowments of human capital drawn from distributions that vary by their birth country. Occupations are differentiated by how intensively they use each of the available skills: cognitive ability is useful in any occupation, but more useful for some than others. The model is characterized by a principle of comparative advantage: workers tend to choose the occupations that use their abundant skills intensively.

I use this principle of comparative advantage to estimate immigrants' skill endowments in three steps. First, I measure the skill intensity of 453 occupations using the O*NET 12.0 Database, the successor to the older Dictionary of Occupational Titles (DOT).[3] From the large set of measured occupational attributes I construct skill intensity measures for five dimensions of skills: education, training and experience, cognitive ability, physical skills, and language and communication skills. Second, I use the 2000 U.S. Census to measure the probability that workers born in 131 countries choose each of these 453 occupations. The U.S. Census is ideal because it offers a large, representative sample with many immigrants and an occupational coding scheme that matches with the O*NET Database.

[3]In addition to the immigration studies listed below, O*NET data has also been used previously to identify the determinants of jobs that might be outsourced (Jensen and Kletzer 2007, Blinder 2009, Costinot, Oldenski, and Rauch 2009, Ritter 2008), to understand the wage differential between part-time and full-time workers (Hirsch 2005), and to measure the wage returns to underlying skills (Abraham and Spletzer 2009). Previously, the DOT was used by labor economists and social scientists in a wide variety of contexts.

Finally, I use logits to estimate the probability that workers born in a particular country choose an occupation as a function of that occupation's five skill intensity parameters. Taken as a whole, the results show that immigrants are more likely to choose cognitive ability-intensive occupations and less likely to choose communications and experience/training-intensive occupations, as compared to natives. The model interprets these coefficients as scaled relative endowments of skills, so immigrants are inferred to be abundant in cognitive ability and scarce in communications skills and experience/training, as compared to natives. After controlling for cognitive ability I find they are neither abundant nor scarce in education. I also decompose the results to find the skills of immigrants from English-speaking countries, developed countries, and countries with high rates of unauthorized immigration.

The worker's occupational choice is embedded into a tractable general equilibrium model, allowing for counterfactual simulations of wages paid in each occupation in the absence of immigration. The simulations imply that the median worker experiences a small 0.1% wage gain from immigration, but the distribution is highly skewed. The largest occupation-level wage increase from immigration is 0.3%, while the largest decrease is an order of magnitude larger at 2.8%. Occupations intensive in cognitive ability and occupations that are unintensive in every skill generally have the largest wage declines with immigration, while those intensive in communications have the largest increases. Education and the fraction of immigrants in the occupation's workforce have little effect once the potential reallocation of American workers is considered.

The size of immigrants' impact on native wages is in line with previous estimates in the literature, but comes through different channels. The primary difference is that previous papers have relied on observable measures of skills, particularly education. For instance, Borjas, Freeman, and Katz (1996) differentiate workers by education and estimates that immigration caused at most a 3.25% wage decline, while Borjas (2003) differentiates workers by education and experience and estimates that immigration caused at most an 8.9% wage decline. I simulate a smaller wage impact but more importantly, I find that it works through communications and cognitive ability channels, with no role for education. Ottaviano and Peri (2007) argue that immigrants are imperfect substitutes even within education-experience categories, consistent with the differences along other dimensions of skills estimated here. They find an upper bound of 2.2% wage losses, although Borjas, Grogger, and Hanson (2008) dispute the imperfect substitutability and find larger effects, up to a 4.2% wage loss. My approach is also similar to Card (2001) and Orrenius and Zavodny (2007), which both treat the occupation-metropolitan area as the appropriate labor market. Card (2001) estimates an effect of no more than 3% lower wages from the 1985-1990 immigration flows. Orrenius and Zavodny (2007) estimate an effect of 0.8-5.2% lower wages for manual laborers as a result of the 1994-2000 immigration flows. This paper presents estimates consistent with the long run where workers can freely adjust their occupations, but still finds similar effects.[4]

The most related previous paper is Peri and Sparber (2009). Like this paper, they use O*NET data to characterize immigrants' chosen occupations. They order occupations in terms of their relative interactive to manual content, and find that immigrants tend to specialize in manual occupations, while natives respond to immigration by specializing in interactive occupations. I build a more general model that allows occupations to vary along several dimensions of skills, and to vary in their total skill intensity (rather than just relative skill intensity). Doing so requires that I estimate workers' skill endowments, rather than treat O*NET data as direct information on those endowments. Despite the methodological difference, my findings are qualitatively similar to theirs: immigrants are scarce in communication skills, so workers whose occupations are communications-intensive have little wage pressure from immigration. By studying five skill dimensions I can add new findings: I also estimate that immigrants are abundant in cognitive ability and scarce in experience and training. These dimensions are also important for the wage impact of immigration; my largest simulated wage losses from immigration are in cognitive ability-intensive occupations.

The paper proceeds as follows. Section 2 presents the model. Section 3 illustrates the main properties of the model and the assumptions under which it is estimable. Section 4 introduces the data and estimates the human capital endowments of immigrants. Section 5 conducts the simulations of the wage impact of immigration. Section 6 concludes.

2 A Model of Labor Markets with Many Skills

2.1 Workers and Human Capital

The model is a static representation of the U.S. labor market. There is a unit continuum of workers born in one of I different countries, with mass η^i born in country i. One of these birth countries is the United States; workers born in other countries are immigrants.

Workers have two sources of heterogeneity. First, they have idiosyncratic tastes for each of the J different occupations in which they can work; denote their tastes by $\varepsilon = (\varepsilon^j)_{j=1}^J$.

[4] Borjas (2005) and Peri and Sparber (2008) both provide evidence of the adjustment of high-skilled workers in response to inflows of immigration, consistent with my exercise.

Tastes are assumed to be draws from a common distribution with cdf $G(\varepsilon)$, defined on $(0, \infty)^J$. Second, they have idiosyncratic skill endowments, H. H is an S-dimensional vector rather than a scalar, $H = (h_1, h_2, ..h_S)$. Each dimension denotes a specific type of human capital, which I call a skill, although it may also include abilities, training, or any of the other common notions of human capital. Human capital endowments are drawn from a distribution that varies by country of birth, with conditional cdf $F(H|i)$. This distribution is the object of interest. Skills may vary by country of birth due to differences in early lifetime environments or due to the effects of self-selection and U.S. policy selection acting on the pool of foreign-born workers. Let $F(H)$ denote the unconditional distribution in the population. Both the conditional and unconditional distributions are defined on $[\underline{h}, \bar{h}]^S$, $0 < \underline{h}$.

In choosing their occupation, workers take into account both the wages they will earn and their tastes for the work they will be asked to perform. Taste draws are normalized to represent compensating wage differentials. Workers choose their occupation to maximize the weighted product of wages and tastes:

$$\phi \log(W^j(H)) + \log(\varepsilon^j). \tag{1}$$

Let the indicator $d^j(H, \varepsilon)$ be a dummy variable taking a value of 1 if j is the solution to this problem and a value of 0 otherwise. Workers inelastically supply a single unit of labor to their chosen profession. They spend their wages on consumption $C(H, \varepsilon)$.

2.2 Occupations and Firms

The output of each occupation is a differentiated intermediate commodity used to produce the aggregate final goods bundle. The economy has a large number of price-taking firms. Firms specialize in hiring workers in a single occupation and producing the differentiated output specific to that occupation. For example, law firms hire lawyers and produce legal services.

Each of the J occupations in the economy uses all the available skills of workers, but occupations vary in how intensively they use the skills. A firm that hires $L^j(H)$ workers with human capital H produces

$$Y^j(H) = A^j L^j(H) \Pi_{s=1}^S (h_s)^{\omega_s^j}$$

units of occupation j output, where A^j is occupation j's general productivity which affects all workers equally.[5] ω_s^j is occupation j's s-intensity, the rate at which it uses a worker's endowment of skill s. Occupations vary in which skills they use more intensively: for example, the task data used in Section 4 indicates that chief executive officers use cognitive ability more intensively than construction workers, while the opposite is true for physical skills. However, occupations also vary in their total skill-intensity: for example, chief executive officers use every skill more intensively than public relations managers. Hence, there is no restriction on $\sum_s \omega_s^j$. Since the outputs of different occupations are imperfect substitutes, prices and wages adjust in general equilibrium so that some workers are willing to choose the less skill-intensive occupations.

Firms take the prevailing wages $W^j(H)$ and the prices of their output P^j as given. They choose the quantity of each type of labor to hire to maximize profits for that type of labor:

$$P^j Y^j(H) - L^j(H)W(H). \tag{2}$$

$\int Y^j(H)dF(H)$ is the total production of occupational output j.

Finally, there exists a single price-taking final goods producer. The producer faces prices P^j and purchases quantities of occupational outputs X^j. It aggregates the occupational outputs using a CES production function with elasticity of substitution ψ. It sells its output Y to consumers. The price of the final good is normalized to be the numeraire of the economy. Then the final goods producer chooses the quantity of each of the J intermediates to purchase to maximize profits:

$$\left[\sum_{j=1}^{J}(X^j)^{1-1/\psi}\right]^{\psi/(\psi-1)} - \sum_{j=1}^{J} X^j P^j. \tag{3}$$

2.3 Equilibrium

For the purposes of conducting counterfactual simulations, it is necessary to define the equilibrium conditions of the economy.[6] There are three sets of market clearing conditions

[5] A linear production technology is equivalent to a setup with capital that assumes full adjustment of capital in response to immigration. For example, suppose that firms choose labor of each type H and how much capital to pair with it, $K^j(H)$, to maximize profits given a capital-augmented production function, $(K^j(H))^\alpha(A^j L^j(H)\Pi_{s=1}^S(h_s)^{\omega_s^j})^{1-\alpha} - L^j(H)W(H) - rK^j(H)$. Combining the first-order conditions for capital and labor yields $W(H) = (1-\alpha)A^j\Pi_{s=1}^S(h_s)^{\omega_s^j}\left(K^j(H)/Y^j(H)\right)^{\alpha/(1-\alpha)}$. Wages are the same as the with a linear technology as long as $K^j(H)/Y^j(H)$ is constant across steady states. It is controversial in the literature whether capital does adjust completely; see for instance Borjas (2003) and Ottaviano and Peri (2007).

[6] An equilibrium will exist under three assumptions made below: $\psi > 1$; that $G(\varepsilon)$ be well-behaved; and that the technologies A^j be bounded from 0. Proof available upon request.

for this economy: one condition for output, one condition for each of the occupational goods markets, and one condition for each type of human capital. They are given by:

$$Y = \int \int c(H, \varepsilon) dF(H) dG(\varepsilon) \tag{4}$$

$$X^j = \int Y^j(H) dF(H) \quad \forall j \tag{5}$$

$$L^j(H) = \int d^j(H, \varepsilon) dF(H) dG(\varepsilon) \quad \forall j, H \tag{6}$$

An equilibrium in this economy is a set of prices $(P^j, W(H))$, allocations for the workers, $(c(H), d^j(H, \varepsilon))$, allocations for intermediate goods firms, $(L^j(H), Y^j(H))$, and allocations for the final goods producer (Y, X^j) that satisfy the following conditions:

1. Taking wages as given, workers maximize their objective, (1).
2. Taking prices as given, intermediate firms maximize profits, (2).
3. Taking prices as given, the final goods producer maximizes profits, (3)
4. Markets clear, (4) - (6).

3 Equilibrium Predictions

The equilibrium has two main predictions that are useful for the results that follow. First, labor market outcomes are characterized by specialization motivated by endowments, similar to the Heckscher-Ohlin theory of trade. Workers who are more skill s-abundant are more likely to choose occupations that are s-intensive. This prediction makes it possible to estimate workers' human capital using their occupational choices. Second, the aggregate supply of different skills affects the labor market returns to those skills. This prediction gives the counterfactual simulations their interest: since immigrants affect the relative abundance or scarcity of skills, they affect relative wages.

3.1 Allocation of Workers to Occupations

In equilibrium, the wage offered to worker H if she chooses occupation j is given by:

$$W^j(H) = P^j A^j \Pi_{s=1}^{S} (h_s)^{\omega_s^j}. \tag{7}$$

Workers choose the occupation j that maximizes the product of wages and the idiosyncratic preference for occupation j. I rewrite this as maximization in logs:

$$\max_j \ \phi \log(A^j) + \phi \log(P^j) + \phi \sum_{s=1}^{S} \omega_s^j \log(h_s) + \log(\varepsilon^j). \tag{8}$$

This discrete choice problem can be estimated under a variety of assumption on the cdfs F and G. However, throughout this paper I specialize to a particular choice for G, given in Assumption 1.

Assumption 1 – ***Distribution of Preferences***
$\log(\varepsilon^j)$ is distributed i.i.d according to the Type-I extreme value distribution.

The extreme value distribution means that the problem fits in the probabilistic choice framework or random utility model of McFadden (1974). It allows for clean propositions describing the behavior of the model. However, the driving consideration here is computational burden. Logit models are well-known to be more practical than alternatives such as multinomial probits for estimation with large sample sizes or a large number of choices; I have both.

Given a worker's human capital H, the likelihood that worker chooses occupation j' can be derived from equation (8) and the usual conditional logit choice probabilities:

$$\int d^{j'}(H, \varepsilon) dG(\varepsilon) \equiv q(j'|H) = \frac{\left[W^{j'}(H)\right]^{\phi}}{\sum_{j=1}^{J} \left[W^j(H)\right]^{\phi}} \tag{9}$$

Alternatively, the probability that a worker with human capital H chooses j over j' is given by $[W^j(H)/W^{j'}(H)]^{\phi}$. Hence, ϕ indexes the relative importance of pecuniary and non-pecuniary factors for occupational choices. For $\phi = 1$, workers are twice as likely to choose a job that pays twice as well. As ϕ becomes larger pecuniary differences become more important and workers are more likely to choose the higher-paying occupation.

One convenient result of using the logit framework is that it is straightforward to give the comparative statics results. For this model the key comparative static is the difference in occupational choices of two workers with marginally different skill endowments.

Proposition 1 – ***Abundance-Intensity Matching***
A marginal increase in $\log(h_s)$ makes a worker more likely to work in occupations that are s-intensive and less likely to work in occupations that are not. Intensity is relative to the expected alternative, so that j' is s-intensive if $\omega_s^{j'} > \sum_{j=1}^{J} \omega_s^j q(j|H)$.

The proposition comes directly from the usual marginal effects equation in a conditional logit model.[7] It is the analogue to the Heckscher-Ohlin Theorem in trade: workers who are more s-abundant are more likely to choose s-intensive occupations. The model accommodates two possible dimensions of comparative advantage. First, the usual one: workers relatively more abundant in a particular skill are more likely to choose occupations that are relatively more intensive in that skill. Second, workers who are more abundant in all skills are more likely to choose occupations that are more intensive in all skills. Hence, the model supports both horizontal and vertical differentiation of occupations, making it possible to infer the relative and absolute skill abundance of workers from their occupational choices.

When comparing the skills of workers in a given cross-section it is possible to hold prices and wages constant. An important and related question is what would happen to prices and wages if all workers became more s-abundant. Proposition 1 is inherently cross-sectional, so it offers little guidance to these questions. The next section provides a general equilibrium result.

3.2 Prices and Wages in General Equilibrium

Changes in the aggregate supply of different bundles of skills affect the relative prices and wages of the various occupations. To describe how, it is useful to define a pairwise notion of comparative advantage in this model. Workers with human capital H are said to have a comparative advantage in occupation j (as compared to workers with human capital H' and occupation j') if:

$$\frac{\Pi_{s=1}^{S} h_s^{\omega_s^j}}{\Pi_{s=1}^{S} h_s^{\omega_s^{j'}}} > \frac{\Pi_{s=1}^{S} (h'_s)^{\omega_s^j}}{\Pi_{s=1}^{S} (h'_s)^{\omega_s^{j'}}}.$$

Comparative advantage here means that workers with H have a higher relative productivity (in j, as compared to j') than workers with H'.

It is intuitive that an increase in the relative abundance of workers with human capital H should lower the relative prices and wages of the occupations in which they have a comparative advantage. This happens for two reasons. First, workers with human capital H are more likely to work in occupations in which they have a comparative advantage, increasing labor supply. Second, they are relatively more efficient producers of H. Both effects work to increase the relative supply of the good and, given the CES aggregator, lower its price and wages. The equation for the relative prices of any two goods in this

[7] The exact equation is $\frac{\partial q(j'|H)}{\partial \log(h_s)} = \phi q(j'|H) \left[\omega_s^{j'} - \sum_{j=1}^{J} \omega_s^j q(j|H)\right]$

economy summarizes the two effects:

$$\frac{P^j}{P^{j'}} = \left[\frac{A^j \Pi_{s=1}^S h_s^{\omega_s^j}}{A^{j'} \Pi_{s=1}^S h_s^{\omega_s^{j'}}}\right]^{-(1+\phi)/(\psi+\phi)}. \tag{10}$$

In the simplifying case where the human capital endowment of all workers in the economy is changed symmetrically, equation (10) is sufficient to show that changes in human capital affect relative wages in the expected manner. Proposition 2 follows directly from equation (10).

Proposition 2 – ***Skill Abundance, Prices, and Wages***
Suppose that all workers in the economy initially have human capital H, but are replaced by workers with human capital H'. Then for occupations in which H offers a comparative advantage, relative prices and wages will rise; for occupations in which H' offers a comparative advantage, relative prices and wages will fall.

Aggregate skill abundance affects wages and prices. Since immigrants have different skills than the average American-born worker, they affect the aggregate skill abundance in the U.S. and hence wages and prices.

4 Empirical Strategy

If it were possible to observe directly workers' human capital endowments along the relevant dimensions, it would be possible to test the model's predictions and estimate the impact of immigrants on wages. But for several measures, such as physical skills or cognitive ability, there is little or no information. Instead, I use the model to estimate the implied human capital endowments of workers. This estimation involves four steps. (i) Use the O*NET Database to characterize the skill intensity ω_s^j of occupations along five skill dimensions. (ii) Use the 2000 U.S. Census to measure the probability that immigrants from 131 birth countries choose each of the 453 occupations, $q(j|i)$. (iii) Use a logit model to estimate $q(j|i)$ as a function of ω_s^j, interacted with country of birth dummies. The estimated logit coefficients measure the sensitivity of immigrants born in country i to occupational intensity in skill s when making occupational choices. The model interprets these coefficients as $\phi \log(h_s^i/h_s^{US})$, the normalized relative endowment of skill s. (iv) Use data on the variability of wages to calibrate ϕ. Then it is possible to measure relative skill endowments, $\log(h_s^i/h_s^{US})$. The following three sections lay out the strategy in more detail.

4.1 Data

The data for this project are taken from two sources. Data on the occupations and characteristics of immigrants come from the 5% sample of the 2000 U.S. Census, drawn from the IPUMS-USA system (Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander 2004). The Census asks every respondent to list their country of birth. For privacy reasons, it aggregates this data so that no birthplace with fewer than 10,000 immigrants is reported separately. After aggregation, there are observations for 131 different birthplaces, including the United States. Some of the birthplaces are nonstandard; for instance, there are response categories for Czechoslovakia, the Czech Republic, and Slovakia, since immigrants may have departed before or after the split. I preserve every statistical entity which is separately identified, and refer to them as countries as a shorthand.[8]

The sample includes workers 18-65 who were self-employed or worked for wages in the previous year. It includes only those who immigrated to the U.S. at age 18 or later. These immigrants likely have skill endowments influenced more by their birth country and selection; for younger immigrants, it is plausible to think that their endowments also reflect the United States environment. The resulting sample is quite large, with half a million immigrants and five million Americans; there at least 139 workers from every country. Finally, the Census provides information on the occupations of workers based on the Standard Occupation Classification (SOC) system, although they merge some occupation codes together. The Census version of the SOC includes 501 occupations; of these, 25 represent "other" or "miscellaneous" categories and are too broad to be used. After discarding these there are 476 well-defined occupations.

Data on the underlying characteristics of occupations are derived from the O*NET database version 12.[9] The O*NET database is the continuation of occupational characteristic descriptions formerly provided in the Dictionary of Occupational Titles (DOT), which was last updated in 1991.[10] It is carried out in partnership with the U.S. Department of Labor. The O*NET database includes information on 812 SOC occupations. I use the provided crosswalk to merge O*NET information into Census occupation codes. When two or more occupations are merged I weight their underlying characteristics using employment from the May 2004 Occupational Employment Statistics Survey from the BLS;

[8]There are two exceptions to this policy. First, I merge the United Kingdom together. Second, the Census coding of Russia and USSR combines immigrants from many smaller former Soviet countries which are not separately identified. I discard Russia and USSR rather than aggregate the entire former USSR into a single observation. The count of 131 already includes these reductions in sample size.

[9]Occupational Information Network (O*NET) and US Department of Labor/Employment and Training Administration (USDOL/ETA) (2007).

[10]U.S. Department of Labor, Employment, and Training Administration (1991).

earlier surveys did not measure employment for all relevant occupations.[11] There are 453 matched occupations with all the necessary information. No information was collected for the military occupations, and some or all of the task data was missing for miscellaneous occupations such as legislator.

The O*NET database contains data on over 250 attributes for each occupation, rated either by professional analysts or current incumbents to the occupation. Most attributes are measured along two dimensions: the importance of the attribute to the job, and the level of the attribute required. Since the goal of the estimation is to measure the skill endowment, I use the level rather than the importance of the attribute. For example, oral expression is important for both lawyers and telemarketers, but lawyers speak at a higher level than telemarketers. For inferring workers' skill endowments, the latter is a more meaningful comparison.

Some of these attributes are not useful for the task at hand (exposure to radiation in the job, or artistic interest of the workers). After removing these, there is still a large number of detailed, highly correlated attributes. Rather than work with these many attributes from the bottom up, this paper takes a top-down approach. The goal is to measure broad dimensions of skill intensity and skill endowment. The previous literature has focused mostly on education, experience, and linguistic skills; the O*NET database provides sufficient information to pursue these dimensions here. To these, it adds enough attributes on cognitive ability and physical skill intensity to measure skills along these two new dimensions. There is not enough information to measure other potentially relevant dimensions, such as ability to speak multiple languages or internal motivation.

For each skill dimension I select between seven and twenty-eight attributes in the O*NET database. I treat these attributes as proxies for the true underlying skill intensity. Education intensity is constructed using measures of requirements for knowledge of subjects taught primarily in high school and college. Experience/training intensity is constructed using measures of requirements for training done in different contexts and observed experience levels. Cognitive ability intensity is constructed using measures of ability to reason and think originally. Physical skill intensity is constructed using measures of strength, coordination, and dexterity; it measures physical skills rather than pure physical strength. Communication intensity is constructed using measures of frequency and types of communication required. Appendix A.1 provides further details. I use principal component analysis (PCA) to extract the first principal component, the one-dimensional variable that captures the highest fraction of the variation in the set of proxies. The first component normalized

[11] Bureau of Labor Statistics (2004).

to lie on the $[0,1]$ interval is used as ω_s^j for the rest of the paper.

I provide three checks on the constructed intensity measures. Tables 4 - 8 provide the comprehensive list of data used to construct each skill intensity, as well as the highest and lowest scoring occupations along each dimension. Visual inspection suggests the rankings of occupations are reasonable. Appendix A.2 shows that observable proxies for workers' skill endowments correlate well with the skill intensities of their chosen occupations, i.e., educated workers choose occupations identified by this process as education-intensive and so on. Section 4.3 shows that the skill intensities lead to reasonable model-predicted wages, and that the main qualitative results are robust to many details of the construction of the ω_s^j.

4.2 Estimation

The main object of interest here is $F(H|i)$, the conditional distribution of human capital given country of birth. The propositions of Section 3 are general across different distributions of F. However, to make estimation tractable it is useful to make parametric assumptions about F. I consider the simplest assumption, that all workers from a given country share the same human capital endowment. In this case the probability that an immigrant from country i chooses occupation j' in equation (9) can be rewritten as:

$$q(j'|i) = \frac{\exp\left[\phi\log(P^{j'}) + \phi\log(A^{j'}) + \phi\sum_{s=1}^{S}\omega_s^{j'}\log(h_s^i)\right]}{\sum_{j=1}^{J}\exp\left[\phi\log(P^{j}) + \phi\log(A^{j}) + \phi\sum_{s=1}^{S}\omega_s^{j}\log(h_s^i)\right]}.$$

This function has the form of a conditional logit (McFadden 1974).[12]

For estimation, the left-hand side variable is the observed probability $q(j'|i)$. The right-hand side variables are a set of occupation fixed effects, which capture occupation characteristics common to all workers, $\phi\log(P^{j'})+\phi\log(A^{j'})$; and the constructed intensity measures $\omega_s^{j'}$ interacted with country of birth dummies, which capture $\phi\log(h_s^i)$. As is standard, it is not possible to include a full set of occupation dummies or country of birth-skill intensity interactions because of collinearity. Hence I exclude one occupation dummy and all of the U.S. interactions. Since the numeraire has already pinned down prices, excluding

[12]An earlier working paper (available on request) also estimated a mixed logit, which has two benefits. First, it is possible to estimate the distribution of skills for workers from country i, rather than assuming all workers have the same skills. Second, conditional logit estimation imposes the independence of irrelevant alternatives (IIA) assumption, which is probably implausible for occupations; the mixed logit relaxes that assumption. However, the distributions estimated by the mixed logit had means similar to the point estimates here, so they yielded little additional insight.

an occupation dummy is equivalent to normalizing technology levels A^j. Excluding U.S. birth-skill interactions means that the coefficients for other countries capture relative skills, $\phi \log(h_s^i/h_s^{US})$.[13]

Estimation is performed via maximum likelihood. The likelihood ratio index for the test comparing the model to an alternative specification with only occupation-specific dummies is 0.00464. The estimates of $\phi \log(h_s^i/h_s^{US})$ for all countries and skills are given in Table 10. In the next section I show how to use wages to pin down ϕ and to test the fit of the model.

4.3 Estimates and Wage Comparisons

The model estimates the probability that workers born in country i choose occupation j as a function of occupation j's technological intensity characteristics, implicitly assuming that better matches $\sum_{s=1}^{S} \omega_s^j \log(h_s^i)$ result in higher wage offers, leading to the observed occupational choices. As a check on the fit of the model and the constructed measures of skill intensity, I compare actual wage differences to the normalized, model-predicted wage difference $\phi \log(W^{i,j}) - \phi \log(W^{US,j})$. I measure wages in the data using a restricted version of the earlier sample. In particular I use only full-time full-year workers, measured as those who worked at least 30 hours a week for at least 30 weeks. The sample is also restricted to workers with positive wage and salary income. Wages are taken to be the average log hourly wage for country of birth-occupation cells with 30 or more workers; restricting the size to 10 or more yields similar but slightly noisier results.

There are 2,848 cells with 30 or more observations in the sample. ϕ is set to 6.99 for the rest of the paper so that the variance of within-occupation wage differences is the same in the model and the data. Recall that ϕ is the parameter governing the relative importance of pecuniary to non-pecuniary factors; this value implies that a worker is 99.2% likely to choose a job that pays twice as well.[14]

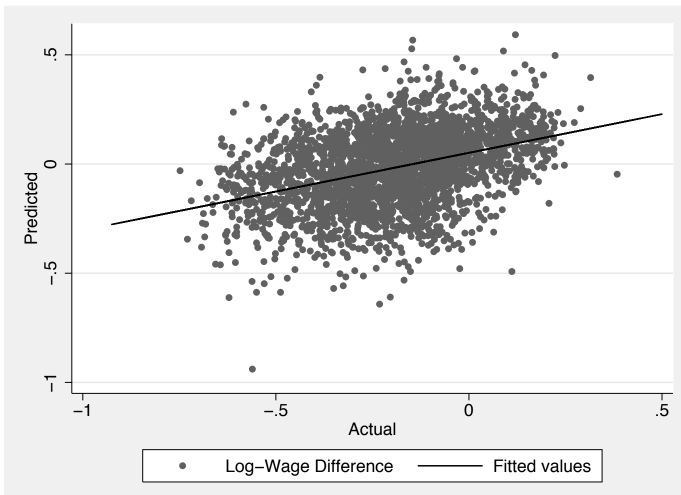
Figure 2 plots the model-implied versus data wage differences. The raw correlation is 0.39. Interpreted as a regression, the model-predicted wages are a statistically significant regressor accounting for 15% of the total variation. A useful comparison is the predictive

[13] Excluding U.S.-skill interactions also changes the interpretation of occupation fixed effects, which formally correspond to $\phi \log(P^j) + \phi \log(A^j) + \phi \sum_{s=1}^{S} \omega_s^j \log(h_s^{US})$. Since the occupation fixed effects are not of interest, this fact can generally be ignored.

[14] By comparison, the same conditional logit can be estimated using less economically meaningful occupational attributes, in which case the estimates should be less useful in predicting occupational choices and wages. Then the estimated ϕ should be smaller, indicating a larger role for "other" factors. Indeed, running such a regression using measures of exposure to five different on the job hazards yields just such a result. In this case $\phi = 3.8$, indicating that a job that pays twice as well is only 93% likely to be chosen, and other characteristics play a substantial role.

power of the development status of the immigrant's birth country. The log of GDP p.c. differences between the birth country and the U.S. predicts only 4.1% of the wage variation, consistent with Hendricks (2002). A regression with a full set of 130 country of origin dummies accounts for 41% of the variation, while a regression with a full set of 453 occupation dummies accounts for 32% of the variation.

Figure 2: Predicted and Actual Wage Differences



Note: Figure displays the average wage difference between natives and immigrants in each of 2,848 country of birth-occupation cells containing 30 or more immigrants in the data.

That a univariate predicted wage derived from the model and constructed intensity scores predicts 15% of actual wage variation and outperforms GDP p.c. by a factor of 4 suggests the model is capturing information about the skills and wages of immigrants. Using wages as a secondary check also provides a simple metric to compare alternative schemes for constructing the skill intensity measures that are used as data in the analysis. I experiment with using simple averages instead of PCA measures; using only four of the components of human capital; changing the underlying set of skills used in the PCA analysis; changing the shape of the PCA-derived measures; and using population percentiles rather than raw scores as inputs to the PCA analysis. These many changes yield similar results, typically accounting for 11-17% of the total wage variation.

Given ϕ, it is possible to transform the logit estimates of $\phi \log(h_s^i/h_s^{US})$ in Table 10 into economically meaningful numbers. In particular, the item of interest is $(h_s^i/h_s^{US})^{\omega_s^j}$, the productivity difference between immigrants and natives due to differences in s endowments. Scaling by ω is important: while it is not clear what it means to say that workers born in

i have "twice as much" physical skills as workers born in the U.S., $(h_s^i/h_s^{US})^{\omega_s^j} = 2$ says workers born in i are twice as productive as workers born in the U.S. on the basis of their s-abundance. These numbers are sensitive to the choice of occupation, j; throughout, I use the population-weighted mean intensity.

Rather than provide 650 separate estimates, Table 1 gives weighted averages for all immigrants and various subgroups of immigrants. Taken as a whole, immigrants are scarce in experience/training and particularly in communications skills; their relative scarcity of communications alone makes them 3% less productive in the average occupation. On the other hand they are abundant in cognitive ability. After controlling for cognitive ability, education seems to explain little of workers' occupational choices, leading the model to infer that immigrants and natives generally have similar education endowments.

Table 1: Relative Skills of Immigrants as Compared to Natives

	Skill Dimension				
	Communications Skills	Experience & Training	Cognitive Ability	Physical Skills	Education
All Immigrants	-3.3%	-1.2%	0.7%	0.1%	0.1%
Panel A: Relative Skills of Likely Authorized/Unauthorized Immigrants					
Authorized	-2.7%	-1.2%	1.7%	-0.5%	0.2%
Unauthorized	-4.4%	-1.3%	-1.0%	1.1%	0.0%
Panel B: Relative Skills of Immigrants from Developed/Developing Countries					
Developed	-1.6%	-0.5%	1.6%	-0.7%	0.2%
Developing	-3.8%	-1.4%	0.4%	0.3%	0.1%
Panel C: Relative Skills of Immigrants by Language of Birth Country					
English	-2.2%	-1.7%	2.3%	-0.5%	0.5%
Other	-3.7%	-1.1%	0.1%	0.4%	0.0%
Panel D: Relative Skills of Early/Recent Immigrants					
Pre-1990	-2.8%	-0.9%	0.7%	0.1%	0.1%
1990+	-3.2%	-1.3%	0.4%	0.2%	0.1%

Notes: Table gives estimated relative skills of different groups of immigrants, as compared to natives. Skill differences are normalized to represent productivity differences in the average occupation. Unauthorized immigrants refers to all immigrants from the fifteen countries with the highest rate of unauthorized immigrants; authorized are all immigrants from other countries. Developed countries are all countries with PPP GDP per capita exceeding one-third the U.S. level (about $13,000) in 2005. English is considered a language in the birth country if it is an official language of the country.

Aggregate numbers mask substantial heterogeneity. Although it is not possible to identify whether or not individuals were unauthorized immigrants, it is well-known that the rate of unauthorized immigration varies by birth country. Table 1 also breaks out the skills of immigrants from the fifteen countries with the highest rates of unauthorized immigration, and of immigrants from all other countries; I refer to these as the authorized and unauthorized countries for convenience.[15] Immigrants from both types of countries are scarce in communications skills, but more so for immigrants from unauthorized countries. The large dichotomy between these two groups is in the abundance of cognitive ability and physical skills. Immigrants from authorized countries are highly abundant in cognitive ability, while immigrants from unauthorized countries are scarce in cognitive ability. The opposite is true of physical skills, with immigrants from unauthorized countries highly abundant and immigrants from authorized countries scarce.

The table also decomposes the results into those attributable to immigrants from developed and developing countries, where developed countries are those with PPP GDP per capita greater than one-third the U.S. value in 2005.[16] Most immigrants are from developing countries even by this relatively generous standard. Overall, immigrants from developed countries and immigrants from authorized countries have similar skills, and likewise for immigrants from developing countries and immigrants from unauthorized countries. The largest difference is that immigrants from developing countries are abundant in cognitive ability while immigrants from unauthorized countries are scarce. This fact suggests that it is the selection inherent in authorized immigration to the U.S. that results in high cognitive ability.

Given that immigrants are so scarce in communication skills, it is worth asking whether the results are simply capturing the language barrier. Panel C distinguishes between im-

[15]The estimated rates of unauthorized immigration are taken from Office of Policy and Planning U.S. Immigration and Naturalization Service (2003). The countries are Mexico, El Salvador, Guatemala, Honduras, Dominica, Bolivia, Brazil, Colombia, Ecuador, Venezuela, Liberia, Nigeria, Sierra Leone, Kenya, and Western Samoa. The estimated rate varies from 52% (Mexico) to 23% (El Salvador). Mexico dominates the group, so 46% of the total group is estimated to be unauthorized. The Department of Homeland Security also provides estimates for a smaller set of countries; their estimates indicate that over two-thirds of the unauthorized immigrants in the United States come from these fifteen countries (Hoefer, Rytina, and Campbell 2007).

[16]Income data from Heston, Summers, and Aten (2009). For some countries income imputation was required, but none were near the cutoff point.

migrants born in countries where English is an official language and immigrants born in countries where it is not. Immigrants born in English-speaking countries are still communications-scarce, although less so, suggesting that language is not the only barrier. Looking at individual country results in Table 10, even Canadian and British immigrants are communications-scarce. Only one country has a statistically significant estimate of communications-abundance (Jordan). Evidently cultural factors matter as much for communication as linguistic barriers.

The final results of this section are designed to allay some concerns about the estimation strategy. The model and estimation both assume that an immigrant's occupation reveals information about their skill endowment. To the extent that this assumption is violated, it is incorrect to interpret the logit coefficients as measures of immigrants' relative skills. Two potential violations seem particularly important. First, it is possible that immigrants' skills evolve over time, or that immigrants' occupations at arrival are not the best possible match (given legal or regulatory barriers). The tendency for immigrants' wages to rise faster than those of natives (assimilation) adds support to this possibility (Borjas 1999). To test for the importance of arrival date, I split the sample into immigrants who entered the United States before 1990, and those who immigrated during or after 1990. This dividing line splits the immigrant sample nearly in half. I then re-estimate the conditional logit on each sample. Panel D shows that the estimated skills of early and late-arriving immigrants are nearly identical. This data is at least consistent with the notion that skills evolve little over time. However, it is also possible that large changes in skills are exactly offset by composition effects, such as changes in immigrant quality or selective outmigration.

A second concern is the evidence that immigrants' occupational choices are driven in part by network effects (Patel and Veila 2007). Network effects could be innocuous if networks primarily function to help immigrants find a job that matches well with their skills. On the other hand, if network effects lead immigrants to choose occupations that fit poorly with their skills simply because previous generations chose those occupations, then the estimates of this paper will be biased. To test for the importance of network effects, I look at the occupational choices of immigrants with weak networks. The idea is that (for example) new Mexican immigrants to California have many previous immigrants nearby who supply them with information and advice that may affect their occupational choice. I discard this information and look instead at the occupational choices of Mexican immigrants in Montana and West Virginia, where there are few previous Mexican immigrants to affect decisions.

I measure an immigrant's network as the share of their state's population born in the same country, and define their network as weak if less than 0.3% of the state's population is from the same country. This cutoff leaves about one-third of immigrants, including some from each of the 130 countries. I then repeat the estimation for this subsample. The logit point estimates are highly correlated with the baseline estimation (greater than 0.93 for each skill) with similar magnitudes. These estimates seem to rule out biases from at least this type of network effects, although they could operate through other channels.

5 Counterfactual Experiments Using Measured Skills

The estimates from the previous section suggest immigrants raise the average level of cognitive ability and lower the average level of communications skills and experience/training in the labor force. Further, there is substantial heterogeneity in the bundles of skills offered by immigrants from different countries. In this section I simulate the wage distributions that would have prevailed if immigration had been prevented, or if immigration from the countries with high rates of unauthorized immigration had been prevented. The latter experiment correlates with but is not exactly the same as preventing unauthorized immigration. By comparing actual to counterfactual distributions I can simulate the wage impact of immigration. These comparisons are made at the occupation level, simulating whether wages paid to a particular occupation would tend to rise or fall. For most comparisons I weight each occupation by its current native employment, so that results are given for the median worker rather than the median occupation.

The results are given as real wage changes, taking account of the changing prices of the consumption bundle. They are similar to comparing steady-state or long-run outcomes and abstract from the dynamics along the transition path. The transition path involves some workers switching occupations, which likely involves further costs not modeled here. Cohen-Goldner and Paserman (2004) and Card (1990) both provide evidence of transition path dynamics in response to a large inflow of immigration; the former finds larger wage effects in the first few years.

There are three primary determinants of the magnitude of the wage impact of immigration. First, the fraction of each occupation's labor force that is foreign born varies (see Figure 1). Occupations with larger immigration inflows tend to have larger wage losses. Second, Americans can substitute into and out of the various occupations in response. Occupations with skill intensities that complement the skill endowments of Americans will have more substitution and smaller wage changes. Finally, the wage impact depends on the elasticity of substitution ψ between the outputs of the various occupations. Immigration affects the relative quantity of labor input supplied and output produced in different occupations. As the elasticity of substitution between occupations increases, these changes in relative output have less of an impact on prices and consequently on wages.

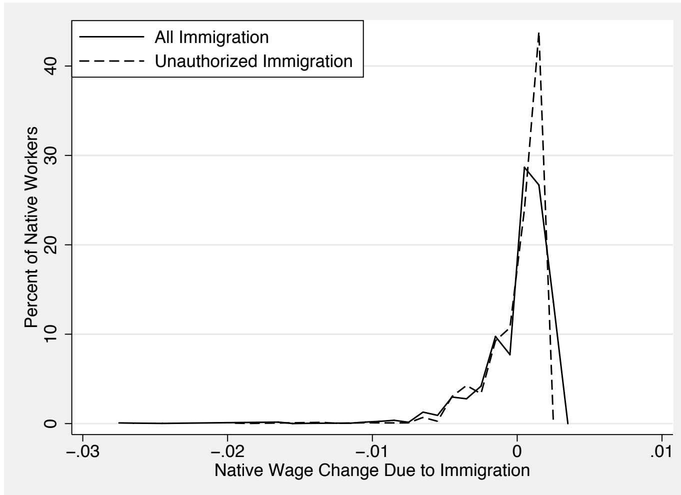
The most relevant previous estimates of ψ are an elasticity of 2.5 between professionals and non-professionals (Chiswick 1978); an elasticity of substitution of 4.1 between blue and white collar workers (Dougherty 1972); and an elasticity of 5-10 between six broad occupation categories (Card 2001).[17] Since occupations here are more finely coded than in Card's work, the elasticity is likely be higher. Results are presented for a range of ψ from 2.5 - 40, with 10 taken to be an intermediate baseline. The major qualitative features of interest do not vary within the range of reasonable ψ, although the exact quantitative magnitudes are sensitive to this parameter.

5.1 Distributional Implications

The primary finding from the wage simulations is that the wage impact of immigration is strongly skewed. This effect shows up most clearly in Figure 3, which plots the distribution of wage changes across occupations for the baseline case where $\psi = 10$. The weighted

[17] See also Hamermesh (1993), which overviews much of the literature estimating labor demand elasticities.

Figure 3: Distribution of Immigration's Impact on Native Wages



Note: Figure is two histograms plotted as line graphs to facilitate comparison. Occupations are weighted by native employment. Unauthorized immigrants refers to all immigrants from the fifteen countries with the highest rate of unauthorized immigrants

median occupation has slightly higher wages due to immigration, but the length of the left tail far outweighs that of the right tail. The simulated wage impact of unauthorized immigration is similar in shape, but the effects are smaller overall. Simulated wage effects are also given in Table 2 for a wide range of ψ. For $\psi = 10$, immigration and unauthorized immigration raise the wage in the weighted median occupation by 0.1%. The largest wage increase is an order of magnitude smaller than the largest wage decrease: 0.3% versus 2.8% for all immigrations, and 0.1% versus 2.0% for unauthorized immigrants.

The shape of the wage distribution is constant across a wide range of elasticities of substitution. However, the magnitudes vary. As outputs of different occupations become better substitutes, prices and wages respond less to the experiments, leading to smaller magnitudes. Figure 4 shows the full distribution for the highest and lowest values of ψ and the compression of wage impacts as the elasticity of substitution rises.

The baseline estimate of 2.8% of the largest change agree with Card (2001), who finds estimates for unskilled workers of 2-3%. Even if the elasticity of substitution were implausibly low - as low as that between professionals and non-professionals - the largest wage change is still predicted to be just 4.9%. Overall, the distributional effects suggest that immigration has very small positive effects for most workers, but large negative effects for workers in a few occupations or with certain types of skills. In the next section, I study the characteristics of those occupations with higher and lower wages.

Table 2: Immigration's Impact on Native Wages

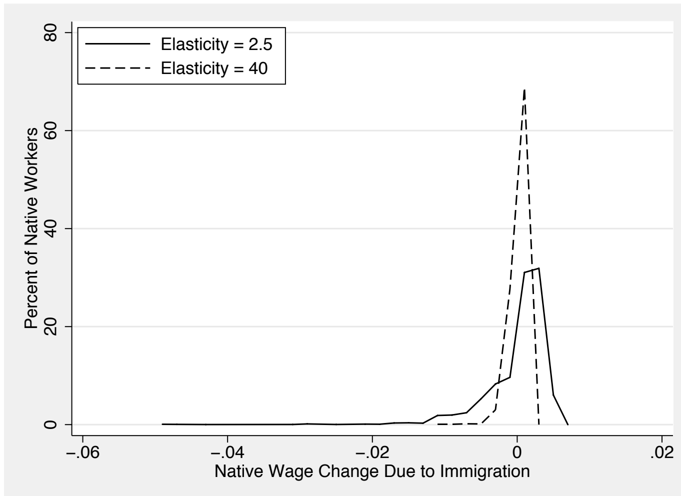
	ψ				
	2.5	5	10	20	40
Panel 1: Wage Impact of Immigration					
Min	-4.9%	-3.9%	-2.8%	-1.8%	-1.0%
Median	0.1%	0.1%	0.1%	0.0%	0.0%
Max	0.5%	0.4%	0.3%	0.2%	0.1%
Panel 2: Wage Impact of Unauthorized Immigration					
Min	-3.5%	-2.8%	-2.0%	-1.3%	-0.7%
Median	0.2%	0.1%	0.1%	0.1%	0.0%
Max	0.3%	0.2%	0.1%	0.1%	0.1%

Notes: Table gives estimated effect of immigration on wages paid by occupations. For median, occupations are weighted by number of Americans in each occupation in 2000 U.S. Census sample. Unauthorized immigrants refers to all immigrants from the fifteen countries with the highest rate of unauthorized immigration.

5.2 Identifying Which Occupations Lose

Finally, what are the characteristics of occupations that gain and lose the most in these simulations? Qualitatively, a broad set of occupations are estimated to gain from immigration, but particularly communications-intensive occupations such as managers, inspectors, and supervisors, and trade occupations such as repairmen, riggers, and boilermakers. The communications and certification/training requirements of these occupations insulate them from immigrants; the primary impact for them is lower prices for their consumption bundle. Those who lose most (the left tail) are broadly occupations using little of any skill, or using only physical skills. For instance, textile pressers, tire builders, dining room and cafeteria attendants, shoe machine operators, and textile machine operators are among the ten

Figure 4: Distribution of Immigration's Impact on Native Wages, Elastic and Inelastic Cases



Note: Figure is two histograms plotted as line charts to facilitate comparison. Occupations are weighted by native employment. Unauthorized immigrants refers to all immigrants from the fifteen countries with the highest rate of unauthorized immigrants

occupations with the largest simulated losses. The simulated effects of only unauthorized immigration are similar on these dimensions. One striking fact stands out: the fraction of an occupation's labor force that is foreign born is only weakly correlated with wage changes, because of the potential for reallocation. Hence, some occupations with over a quarter of the work force foreign born still see wage effects of less than one tenth of a percent for $\psi = 10$, including diverse occupations such as taxi drivers, chefs, and economists.

A smaller group of occupations with significantly lower wages is those with high cognitive ability intensity and low communications intensity, including aerospace engineering (largest loss), dietitians (22nd) and astronomers and physicists (23rd). Many immigrants appear to possess abundant cognitive ability, and are apt to enter these occupations where language is less of a barrier. The model treats this increase in supply as a pure increase in competition and predicts significantly lower wages. However, an important caveat applies. An influx of highly cognitively able immigrants also provides benefits through knowledge spillovers, such as those modeled formally by Lucas (1988) or Ehrlich and Kim (2007). It is not hard to imagine that the competition effect for physicists, for example, is mitigated or entirely offset by the increased production through these spillovers. In this case immigration would have less of an effect on wages, and could even potentially have a positive effect if spillovers are large enough. Since spillovers are difficult to measure empirically and likely apply mostly to cognitive ability, they are abstracted from here.

Table 3 explores the determinants of wage changes more systematically. The first column contains the results from regressing an occupation's simulated wage change from immigration on the occupation's skill intensity parameters and the fraction of the occupation's workforce foreign born. The second column contains the results from a similar regression using simulated wage changes from unauthorized immigration and the fraction of the workforce that is unauthorized foreign-born. There are sizable effects for some of the skill attributes, particularly cognitive ability and communications. Recall that the skill intensity variables are scaled to lie on $[0, 1]$. The difference between being the cognitively least and most intensive occupations is a 0.9% lower wage from immigration; for communications, the difference is a 2.0% higher wage from immigration. The results quickly summarize that immigration increases the average supply of communications and experience and training and decrease the average supply of communications skills. Note also that the fraction of the work force that is foreign-born has a small and statistically insignificant coefficient. Skill intensity, not immigrant share of the workforce, explains most of the impact of immigration.

The identities of winners and losers from immigration fits well with recent research. Peri and Sparber (2009) find that immigration induces American workers to specialize in interactive occupations - similar to the communications-intensive occupations here. My findings are similar, subject to the caveat that for some workers and occupations, there are no good substitutes available: the occupations similar to aerospace engineer are also not communications-intensive. They also find interesting results about how new cohorts of immigrants impact the wages of older cohorts, which I do not disentangle. Finally, Peri and Sparber (2008) and Borjas (2005) both show that high-skill immigration affects the wages and career decisions of high-skilled Americans. The latter shows that immigration pushes Americans to study communications-intensive subjects in graduate school. This paper adds two novel findings to the previous literature. First, experience and training-intensive occupations limit competition from immigrants in a manner similar to occupations

Table 3: Determinants of Immigration's Impact on Native Wages

	Immigration	Unauthorized Immigration
Communication	2.011***	1.039***
	(0.0699)	(0.0481)
Experience & Training	0.677***	0.274***
	(0.0640)	(0.0445)
Cognitive	-0.962***	0.0832
	(0.0861)	(0.0607)
Physical	0.182***	-0.0720*
	(0.0446)	(0.0313)
Education	-0.306***	-0.196***
	(0.0606)	(0.0425)
Immigrant Share L.F.	0.0118	
	(0.157)	
Unauth. Imm. Share L.F.		-0.345*
		(0.167)
Observations	453	453
R^2	0.724	0.731

Standard errors in parentheses

Dependent variable is estimated percentage wage change from all or unauthorized immigration.

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

intensive in communications. Second, some of the impact on high-skilled Americans is due to the high cognitive ability of immigrants

6 Conclusion

This paper has proposed a theory of labor markets where workers vary in their endowment of a vector of skills, and occupations vary in their intensity over the vector of skills. Comparative advantage leads workers to match their endowments to occupations that are appropriately skill-intensive. Although the theory and estimation is general to a variety of contexts, I use the model to estimate the human capital endowments of immigrants born in 130 countries over 5 skill dimensions. Immigrants are net suppliers of cognitive ability, but are scarce in experience/training and particularly communications skills. The impact of immigration on native wages is skewed, with a small set of occupations offering much lower wages and no occupation offering much higher wages.

The simulated wage impacts of immigration are moderate, even though they miss several factors that may limit them further. The baseline simulation assumes a conservatively low elasticity of substitution across occupations. The simulations ignore, for instance, the ability of Americans to export excess goods as predicted in a Heckscher-Ohlin framework - not all aerospace engineering services are consumed in the United States. They also assume that the endowments of Americans are fixed, but as Peri and Sparber (2008) and Borjas (2005) have shown, Americans change their schooling and human capital accumulation decisions as well. However, they do rest on full adjustment of the capital stock, as opposed to Borjas (2003); if the capital stock does not adjust fully, the simulated wage effects would be larger.

A skewed distribution of wage impacts naturally suggests political economy stories for immigration policy. In particular, this paper offers a novel method to measure the cognitive ability of immigrants, and suggests that authorized immigrants are large net suppliers of cognitive ability, with strong wage effects for cognitive ability-intensive occupations. This may help explain why the allocation of H1-B visas is set “low”. This subject is left for future research.

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A Measures of Skill Intensity

A.1 Information Used

The O*NET database is built on a content model that divides occupational information into six broad categories: worker characteristics, worker requirements, experience requirements, occupation-specific information, workforce characteristics, and occupational requirements. Within each of these six broad categories information is organized in a hierarchical format similar to the 1-digit, 2-digit, 3-digit format of industry and trade data. For instance, item 1.A.1.a.1 is a 5-digit characteristic of occupations, going from general to specific: Worker Characteristics.Ability.Cognitive Abilities.Verbal Abilities.Oral Comprehension. Throughout, I use the most disaggregated data possible, which can be 3 to 6-digit information.

Data are provided for each category and occupation, and is typically normalized to a 0-7 scale. O*NET provides anchors that represent typical characteristics associated with particular scores. For example, Oral Comprehension is computed on a scale of 0-7. The anchors given are that a score of 2 is equivalent to ability to understand a television commercial; a score of 4 is equivalent to ability to understand a coach's oral instructions for a sport; and a score of 6 is equivalent to ability to understand a lecture on advanced physics. Scores for each occupation-attribute are gathered either from the average score given by occupational analysts or the average score given by survey responses from incumbent workers. For instance, all oral comprehension scores are the average rating of eight analysts, while the mathematics skills score for chief executives is the average of 23 survey responses by actual chief executives.

From the 250+ most disaggregated categories I select those that correspond closely to one of the five skills. I also focus on information that is relatively unique to a specific skill. The reported level anchors are helpful here. For example, I exclude oral comprehension ability because it is not clear from the anchors provided whether it measures a cognitive ability, a communication skill, or a mixture. I use principal component analysis to aggregate the different measures into a single skill intensity for each dimension. I keep only the first component, which accounts for 36-82% of the total variation of the variables. In Tables

4-8, I denote with a * variables that have at least one-third of their variation accounted for by the principal component, indicating that they are well-represented in the resulting skill intensity measure. This criteria produces similar results to the common technique of identifying variables that have factor loadings exceeding a threshold of 35 or 40. For each of the five dimensions, I also identify the three occupations that score as the most skill-intensive, and the three that score as the least skill-intensive. No occupation is repeated on this list, and more generally no cross-intensity correlation exceeds 0.60, implying sufficient variation to identify the skill dimensions separately.

A.2 Checks on Intensity Measures

According to Proposition 1, workers who are more s-abundant should choose occupations that are s-intensive. Here, I test whether the prediction holds using the constructed measures of skill intensity. The Census provides some proxies for the skill endowments of workers. I implement the test by regressing:

$$\omega_s^j = b_1 + b_2 \tilde{h}_s + e$$

where ω_s^j is the constructed skill intensity of the worker's chosen occupation and $\tilde{h}_s$ is the proxy for skill endowment. I then test whether b_2 is significant and has the expected sign.

The Census includes variables that can be used as proxies for three dimensions of the skill endowments. Educational attainment is a straightforward proxy for education and knowledge. Likewise, the Census includes self-assessed English language proficiency, a proxy for communication skills. Potential experience is a proxy for experience and training. The other dimensions lack obvious proxies. The sample is the same as the baseline sample of the paper.

Table 9 gives the results. With the large sample, each variable is statistically significant at conventional levels. For communication and education, the effect is also large: these are the two best proxy measures, used fruitfully in the literature. The experience coefficient is smaller. All the coefficients have the expected sign. From these tests I conclude that the constructed measures of skill intensity are reasonable: more educated workers choose occupations measured as education-intensive and so on. The result for education is important in light of the small estimated differences between the education endowments of natives

Table 4: Dimensions of Human Capital: Education and Knowledge

Measure[a]	Intensity Ranking[b]
Knowledge Category	Most Intensive
Engineering and Technology	1. Physicians and Surgeons
Design	2. Miscellaneous Social Scientists
Mathematics	3. Psychologists
Physics	
Chemistry	Least Intensive
Biology*	1. Food and Tobacco Machine Operator/Tender
Psychology*	2. Taxi Driver and Chauffeur
Sociology*	3. Desktop Publishers
Geography	
Medicine and Dentistry*	
Therapy and Counseling*	
Foreign Language*	
Fine Arts	
History and Archaelogy*	
Philosophy and Theology*	
Law and Government*	
Other Category	
Required Education Level*	

[a] Name of measure in O*NET system. An asterisk indicates that the first principal component captures at least 1/3 of the variation in the measure.

[b] Three occupations that score highest and lowest for skill intensity.

Table 5: Dimensions of Human Capital: Training and Experience

Measure[a]	Intensity Ranking[b]
Training and Experience Required	Most Intensive
On-the-Job Training*	1. Elevator Installers and Repairers
Required Work Experience*	2. Ship Engineers
On-Site/In-Plant Training*	3. Podiatrists
General Preparation	
	Least Intensive
Observed Job Experience	1. Ushers, Lobby Attendants, and Ticker Takers
< 1 Year*	2. Telemarketers
1-5 Years*	3. Dishwashers
6-9 Years	
10+ Years*	

[a] Name of measure in O*NET system. An asterisk indicates that the first principal component captures at least 1/3 of the variation in the measure.
[b] Three occupations that score highest and lowest for skill intensity.

Table 6: Dimensions of Human Capital: Cognitive Abilities

Measure[a]	Skill Intensity[b]
Worker Abilities	Most Intensive
Fluency of Ideas*	1. Aerospace Engineers
Originality*	2. Astronomers and Physicists
Problem Sensitivity*	3. Mechanical Engineers
Deductive Reasoning*	
Inductive Reasoning*	Least Intensive
Information Ordering*	1. Miscellaneous Construction Equipment Operators
Category Flexibility*	2. Laborers and Freight/Stock/Materials Movers, Hand
	3. Grinding Tool Setters/Operators/Tenders

[a] Name of measure in O*NET system. An asterisk indicates that the first principal component captures at least 1/3 of the variation in the measure.
[b] Three occupations that score highest and lowest for skill intensity.

Table 7: Dimensions of Human Capital: Physical Abilities

Measure[a]	Intensity Ranking[b]
Worker Abilities	Most Intensive
Arm-Hand Steadiness*	1. Fire Fighters
Manual Dexterity*	2. Electricians
Finger Dexterity*	3. Emergency Medical Technicians and Paramedics
Control Precision*	
Multilimb Coordination*	Least Intensive
Response Orientation*	1. Public Relations Specialist
Rate Control*	2. Actuaries
Reaction Time*	3. Loan Counselors and Officers
Wrist-Finger Speed*	
Speed of Limb Movement*	
Static Strength Ability*	
Explosive Strength	
Dynamic Strength*	
Trunk Strength*	
Stamina*	
Extent Flexibility*	
Dynamic Flexibility	
Gross Body Coordination*	
Gross Body Equilibrium*	
Near Vision	
Far Vision	
Visual Color Discrimination*	
Night Vision*	
Peripheral Vision*	
Depth Perception*	
Glare Sensitivity*	
Hearing Sensitivity*	
Auditory Attention*	

[a] Name of measure in O*NET system. An asterisk indicates that the first principal component captures at least 1/3 of the variation in the measure.

[b] Three occupations that score highest and lowest for skill intensity.

Table 8: Dimensions of Human Capital: Language and Communication

Measure[a]	Intensity Ranking[b]
Frequency of Communication by Method	Most Intensive
Public Speaking*	1. Gaming Managers
Telephone*	2. Postmasters and Mail Superintendents
Letters and Memos*	3. Public Relations Specialists
Face-to-Face Discussions*	
	Least Intensive
Frequency of Communication by Type	1. Pressers, Textile, Garment, and Related Materials
Contact with Others*	2. Tire Builders
Work with Group or Team*	3. Shoe Machine Operators and Tenders
Deal with External Customers*	

[a] Name of measure in O*NET system. An asterisk indicates that the first principal component captures at least 1/3 of the variation in the measure.

[b] Three occupations that score highest and lowest for skill intensity.

Table 9: Test of Constructed Skill Intensity

	Occupation Skill Intensity		
	Communication	Exp/Training	Education
Worker Skill Endowment			
English Proficiency	0.2151***		
	(0.0007)		
Potential Experience		0.0013***	
		(0.0000)	
Educational Attainment			0.4141***
			(0.0011)
Observations	6080718	6080718	6080718

Notes: English proficiency and educational attainment are implemented as dummy variable regressions; reported coefficients are for the highest level (speaks English very well and Doctoral degree), with the lowest level omitted.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and immigrants; it suggests that this result is not due to poor measurement of education intensity.

Table 10: Conditional Logit Estimates of Scaled Relative Human Capital

Country	Obs	Communication	Exp/Train	Cognitive	Physical	Education
United States	5285011					
Puerto Rico	12676	-0.266***	-0.145***	-0.036**	0.025***	0.091***
Canada	10894	-0.08***	-0.026*	0.355***	-0.147***	0.132***
Bermuda	165	0.139	0.119	-0.22*	-0.065	-0.026
Cape Verde	447	-0.596***	-0.161***	-0.135*	-0.034	0.042
Mexico	136866	-0.458***	-0.157***	-0.209***	0.227***	-0.019***
Belize/British Honduras	685	-0.067	-0.208***	0.1	0.067**	0.03
Costa Rica	1250	-0.29***	-0.079**	-0.208***	-0.005	0.117***
El Salvador	14825	-0.462***	-0.156***	-0.245***	0.088***	0.06***
Guatemala	8707	-0.495***	-0.152***	-0.19***	0.1***	0.058***
Honduras	5238	-0.396***	-0.13***	-0.24***	0.138***	0.076***
Nicaragua	3384	-0.268***	-0.137***	-0.16***	0.018	0.022
Panama	1787	-0.029	-0.22***	0.103**	-0.052**	0.044*
Cuba	10009	-0.148***	-0.037***	-0.102***	0.045***	-0.072***
Dominican Republic	9399	-0.348***	-0.299***	-0.006	0.057***	-0.007
Haiti	7832	-0.326***	-0.565***	0.163***	0.167***	0.216***
Jamaica	9882	-0.119***	-0.393***	0.25***	0.142***	0.158***
Antigua-Barbuda	355	-0.099	-0.247***	0.129	0.039	0.127**
Bahamas	336	-0.033	-0.224***	0.106	-0.005	0.122**
Barbados	933	-0.152***	-0.294***	0.063	0.049*	0.218***
Dominica	312	-0.31***	-0.26***	0.163*	0.062	0.208***
Grenada	538	-0.135*	-0.358***	0.246***	0.132***	0.242***
St. Kitts-Nevis	224	-0.161*	-0.227***	0.233**	0.031	0.046
St. Lucia	259	-0.04	-0.163**	0.003	0.121**	0.026
St. Vincent	369	-0.128*	-0.315***	0.156*	0.144***	0.153***
Trinidad & Tobago	3542	-0.102***	-0.284***	0.23***	0.056***	0.067***
Argentina	2173	-0.171***	0	0.114***	-0.105***	0.114***
Bolivia	994	-0.228***	-0.064*	-0.127**	-0.092***	0.08**
Brazil	4329	-0.352***	-0.125***	-0.101***	-0.109***	0.176***
Chile	1442	-0.195***	-0.054*	-0.038	-0.042*	0.141***
Colombia	8987	-0.331***	-0.142***	-0.042**	-0.052***	0.057***

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Table 10: Conditional Logit Estimates of Scaled Relative Human Capital

Country	Obs	Communication	Exp/Train	Cognitive	Physical	Education
Ecuador	4964	-0.351***	-0.137***	-0.082***	0.043***	-0.075***
Guyana/British Guiana	3838	-0.086***	-0.318***	0.261***	0.067***	0
Paraguay	215	-0.496***	-0.021	-0.225*	-0.173***	0.361***
Peru	5495	-0.264***	-0.117***	-0.074***	-0.045***	0.057***
Uruguay	484	-0.169***	0.023	-0.054	-0.047	-0.02
Venezuela	1645	-0.124***	-0.075**	0.158***	-0.129***	0.008
Denmark	511	-0.037	0.058	0.372***	-0.148***	-0.004
Finland	364	-0.106	-0.048	0.51***	-0.115**	0.022
Norway	386	-0.018	0.021	0.451***	-0.122***	0.053
Sweden	879	-0.083*	-0.125**	0.535***	-0.136***	0.036
United Kingdom	11346	-0.056***	-0.024*	0.397***	-0.191***	0.014*
Ireland	2783	0.014	0.095***	0.088***	-0.009	0.022
Belgium	399	-0.149*	-0.033	0.351***	-0.274***	0.107**
France	2477	-0.162***	-0.022	0.333***	-0.252***	0.095***
Netherlands	1159	-0.11**	0.045	0.44***	-0.17***	0.074**
Switzerland	723	-0.207***	0.081	0.454***	-0.232***	0.04
Albania	660	-0.293***	-0.215***	-0.117*	0.016	-0.096*
Greece	2231	-0.08***	-0.152***	0.241***	0.055***	-0.044*
Macedonia	329	-0.226***	-0.074	-0.122	0.152***	-0.178**
Italy	4182	-0.262***	0.064***	0.073***	-0.038***	0.002
Portugal	2638	-0.444***	0.125***	-0.155***	0.038**	-0.056**
Azores	296	-0.451***	0.054	-0.195*	0.112*	-0.104
Spain	1453	-0.229***	0.054	0.037	-0.146***	0.223***
Austria	533	-0.187***	0.053	0.317***	-0.191***	0.127***
Bulgaria	721	-0.267***	-0.173***	0.236***	-0.08**	0.069*
Czechoslovakia	506	-0.266***	0.041	0.162**	-0.061*	0.03
Slovakia	260	-0.227**	0.01	0.057	-0.017	0.036
Czech Republic	414	-0.226***	-0.071	0.143*	-0.016	0.105*
Germany	9144	-0.102***	-0.095***	0.233***	-0.127***	0.02*
Hungary	1016	-0.247***	0.119***	0.25***	-0.085***	-0.004
Poland	7841	-0.367***	0.111***	-0.008	-0.028***	0.009

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Table 10: Conditional Logit Estimates of Scaled Relative Human Capital

Country	Obs	Communication	Exp/Train	Cognitive	Physical	Education
Romania	2264	-0.331***	-0.013	0.351***	-0.06***	0.042*
Yugoslavia	1230	-0.287***	0.027	-0.029	-0.043*	-0.052*
Croatia	642	-0.254***	0.17***	-0.033	-0.012	0
Serbia	173	-0.309***	0.004	-0.033	-0.088	0.011
Bosnia	1846	-0.476***	-0.059**	-0.072*	-0.003	-0.085***
Kosovo	150	-0.27***	-0.154*	-0.253**	0.032	-0.089
Latvia	204	-0.299***	-0.103	0.52***	-0.18***	0.011
Lithuania	262	-0.227**	-0.122	0.458***	-0.03	0.017
Byelorussia	593	-0.255***	-0.145***	0.525***	-0.036	-0.168***
Moldovia	313	-0.191**	-0.045	0.289***	-0.002	-0.088
Ukraine	3915	-0.317***	-0.095***	0.377***	-0.073***	-0.078***
Armenia	821	-0.001	-0.193***	0.133**	0.116***	-0.078**
Azerbaijan	220	-0.273***	-0.142*	0.26**	-0.08	0.051
Georgia	163	-0.265**	-0.289***	0.407***	0.015	0.135*
Uzbekistan	299	-0.328***	-0.131*	0.369***	-0.108**	0.015
China	19090	-0.583***	-0.232***	0.537***	-0.24***	0.09***
Hong Kong	3327	-0.261***	-0.123***	0.43***	-0.261***	-0.095***
Taiwan	6439	-0.243***	-0.03	0.639***	-0.303***	-0.051***
Japan	5764	-0.128***	-0.126***	0.398***	-0.203***	0.025*
South Korea	2000	-0.151***	-0.17***	0.228***	-0.063***	-0.052**
Cambodia	1911	-0.531***	-0.192***	0.27***	-0.016	-0.258***
Indonesia	1150	-0.25***	-0.287***	0.478***	-0.126***	0.009
Laos	2531	-0.705***	-0.088***	0.211***	0.017	-0.295***
Malaysia	1048	-0.253***	-0.19***	0.487***	-0.228***	-0.01
Philippines	29294	-0.27***	-0.363***	0.379***	-0.036***	0.151***
Singapore	393	-0.18**	-0.212***	0.636***	-0.261***	0.026
Thailand	2355	-0.313***	-0.33***	0.323***	-0.058***	0.065***
Vietnam	17344	-0.533***	-0.064***	0.292***	-0.095***	-0.286***
Afghanistan	631	0.051	-0.44***	0.422***	0.127***	-0.163***
India	23130	-0.464***	-0.096***	0.649***	-0.289***	0.096***
Bangladesh	1681	-0.093**	-0.568***	0.491***	0.027	-0.085***

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Table 10: Conditional Logit Estimates of Scaled Relative Human Capital

Country	Obs	Communication	Exp/Train	Cognitive	Physical	Education
Burma (Myanmar)	718	-0.383***	-0.114**	0.38***	-0.086**	-0.052
Pakistan	4114	-0.076***	-0.391***	0.617***	0.046***	-0.079***
Sri Lanka (Ceylon)	642	-0.26***	-0.253***	0.571***	-0.183***	0.14***
Iran	5388	-0.025	-0.077***	0.463***	-0.086***	-0.046***
Nepal	258	-0.383***	-0.456***	0.411***	-0.207***	0.143**
Cyprus	185	-0.288**	-0.004	0.393***	-0.116*	0.054
Iraq	1381	-0.194***	-0.116***	0.221***	0.041*	-0.101***
Israel/Palestine	1861	-0.029	-0.036	0.302***	-0.137***	0.014
Jordan	787	0.129**	-0.293***	0.495***	0.12***	-0.228***
Kuwait	248	-0.024	-0.338***	0.673***	-0.022	-0.062
Lebanon	1860	-0.035	-0.056*	0.419***	-0.056**	-0.059***
Saudi Arabia	139	-0.078	-0.081	0.355***	-0.007	-0.034
Syria	941	-0.032	-0.092**	0.315***	0.033	0.021
Turkey	1456	-0.198***	-0.101***	0.363***	-0.106***	0.054**
Yemen Arab Republic (North)	253	-0.08	-0.448***	0.277**	0.116*	-0.374***
Algeria	240	-0.098	-0.322***	0.397***	-0.042	-0.006
Egypt/United Arab Republic	2232	-0.097***	-0.245***	0.471***	-0.039**	0.06***
Morocco	803	0.057	-0.373***	0.243***	0.035	-0.102**
Sudan	324	-0.333***	-0.446***	0.354***	0.017	0.044
Ghana	1625	-0.203***	-0.546***	0.439***	0.072***	0.151***
Liberia	784	-0.143**	-0.624***	0.437***	0.103***	0.226***
Nigeria	3317	-0.07**	-0.568***	0.647***	0.048***	0.228***
Senegal	212	0.026	-0.34***	0.131	0.028	-0.17**
Sierra Leone	507	-0.083	-0.703***	0.488***	0.131***	0.232***
Ethiopia	1463	-0.048	-0.698***	0.438***	0.103***	-0.09***
Kenya	863	-0.196***	-0.477***	0.511***	-0.127***	0.174***
Somalia	452	-0.325***	-0.51***	0.21***	0.095**	-0.082
Tanzania	268	-0.269***	-0.164*	0.452***	-0.167***	0.128**
Uganda	306	-0.231***	-0.315***	0.517***	-0.08	0.091*
Zimbabwe	247	-0.146	-0.169*	0.498***	-0.108*	0.103*
Eritrea	372	-0.196***	-0.507***	0.353***	0.042	-0.057

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Table 10: Conditional Logit Estimates of Scaled Relative Human Capital

Country	Obs	Communication	Exp/Train	Cognitive	Physical	Education
Cameroon	283	-0.054	-0.628***	0.618***	0.015	0.19***
South Africa (Union of)	1308	-0.021	0.015	0.422***	-0.254***	0.103***
Australia	1227	-0.116***	-0.097**	0.472***	-0.206***	0.109***
New Zealand	560	-0.069	0.053	0.337***	-0.144***	0.086**
Fiji	593	-0.211***	-0.303***	0.239***	0.066*	-0.077*
Tonga	288	-0.282***	-0.118*	-0.046	0.168***	0.008
Western Samoa	254	0.01	-0.067	-0.199*	0.093*	-0.162**

Notes: Reported values are conditional logit estimates for an interaction term between the given country of birth and occupation skill intensity. The model interprets these values as normalized skills, $\phi \log\left(h_s^i / h_s^{US}\right)$. Obs is the number of observations in the 5% sample of the 2000 U.S. Census meeting the sample criteria for that country.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$