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Income Maximization and the Sorting of Emigrants across Destinations

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Abstract. Recent data on emigrant schooling suggests that emigrants are almost universally more skilled than non-emigrants from the same country. For the case of poor source countries and rich destination countries, this runs counter to the negative selection predicted by the Borjas-Roy model of income maximization. We present a different income maximization model that admits positive selection while at the same time making sharp predictions that can be tested with data on immigrants in multiple destination countries. The model predicts that emigrants from a given source country should sort themselves across destination countries according to the rewards to skill among destinations: destinations with larger rewards to skill should receive a higher-skilled mix of immigrants on average than destinations with lower rewards to skill. We test this prediction using data on emigrants from 192 source countries to a dozen OECD destination countries. Our tests are generally consistent with positive sorting. Furthermore, our results show that destination-country immigration policy has important effects on the skill composition of migrants. Economic and policy factors can explain a substantial share of the immigrant skill differences that we observe among destination countries.

1. Introduction

International migration is an increasingly important mechanism for global economic integration. Most migrants leave home bound for rich nations (UN, 2005). In OECD countries the stock of immigrants increased by 37 percent between 1990 and 2000. In the US, the share of the foreign-born in the population rose from 7.9% to 10.8%, while in the EU the foreign-born share rose from 5.3% to 7.0%.

One of the central issues in international labor flows is the skill composition of migrants. The influential Borjas-Roy income-maximization framework (Borjas, 1987; Roy, 1951) implies that migration costs and returns to skill should cause low-skill individuals to dominate migration flows from poor countries to rich countries.¹ Much of the empirical research on negative selection examines the skill levels of immigrants (from various source countries) residing in a single destination country. Such analyses tend to report evidence consistent with negative selection (Borjas, 1999).

Recent work that compares the skills of emigrants to the skills of source-country non-migrants is more mixed. Puerto Rican migrants to the US mainland tend to have low schooling relative to non-migrants (Ramos, 1992; Borjas, 2006), consistent with negative selection. However, Mexican emigrants appear to be drawn from near the middle of Mexico's schooling distribution,² consistent instead with intermediate selection.

Furthermore, recent data suggest that negative selection may be the exception rather than the rule.³ Docquier and Marfouk (2006) document that for the vast majority

¹ On the Roy model and internal migration, see Borjas, Bronars, and Trejo (1992) and Dahl (2002).

² See Feliciano (2001), Hanson and Chiquiar (2005), Orrenius and Zavodny (2005), McKenzie and Rapoport (2006), Cuecuecha (2005), Lubotsky (2005) and Fernandez-Huertas (2006).

³ This perhaps should not come as a surprise. Puerto Ricans face no restrictions on migration to the U.S. mainland and few neighboring countries match Mexico and the United States in terms of the magnitude of their income differences and the length of their land border. Low migration costs to the United States may allow the low skilled in Mexico and Puerto Rico to play a relatively large role in migration abroad.

of source countries, individuals with more education are more likely to migrate abroad. In Figure 1, which plots the share of tertiary-educated emigrants against the share of tertiary-educated non-migrants by source country, nearly all points lie above the 45-degree line. To a first approximation, positive selection of emigrants in terms of schooling appears to be universal. This finding has motivated a recent empirical literature on the economic consequences of brain drain.⁴

Does universal positive selection mean that we should reject income maximization as a model of migration? The answer is clearly no. The prediction in Borjas (1987) that migrants from poor countries should be negatively selected depends on migration costs being fixed in terms of units of time (e.g., migrating from Mexico to the United States requires the same amount of labor time for individuals at all skill levels). Borjas (1991) generalizes this approach to show that if the time lost to migrating varies with an individual's skill level (as would be the case if migration costs are fixed in monetary units) then the relative skills of migrants will depend on the correlation between skill and mobility costs. While this result offers a potential explanation for positive selection, it is disconcerting, since it suggests that income maximization may not generate falsifiable predictions about emigrant selection.

In this paper, we develop an income maximization model that allows for fixed monetary migration costs and is thus consistent with either positive or negative selection. More importantly, the model generates clear predictions about the *sorting* of emigrants across destination countries. It predicts that emigrants from a single source country

⁴ See Carrington and Detragiache (1998), Adams (2003), Beine, Docquier, and Rapoport (2001, 2006a, 2006b), and Docquier and Marfouk (2006).

should choose between destinations in such a way that the destination that rewards skill the most should receive the most educated mix of emigrants.

Our model motivates a sorting regression which, in the presence of multiple destinations, allows us to control for fixed migration costs, and other unobservables, via a set of source-country-specific fixed effects. These effects control more broadly for source-country factors that are specific to a skill group but common across destinations (e.g., the average attractiveness of migrating abroad for individuals in a given location). Source-country dummies also obviate the need to measure source-country economic opportunities. This is of great practical benefit since information on many source-country economies is less rich than information on OECD economies. We test for sorting using a new data set that measures aggregate emigrant stocks in 2000 by skill level from 192 source countries residing in the major OECD destination countries.

Our approach complements Rosenzweig (2007), who examines how skill prices in source countries affect the volume and composition of legal migrants in the US. While his paper uses an income-maximization approach to examine who leaves source countries, we instead examine how migrants of different skill levels sort themselves across destinations. The advantage of our approach is that it allows us to control for fixed migration costs and other source country determinants of migration; the disadvantage is that we cannot evaluate the volume of migration flows explicitly.⁵

Consistent with income maximization, we find positive sorting of migrants across destinations. Controlling for the source country, the relative flow of more-educated

⁵ Other work on international migration tends to examine flows between source-destination country pairs, without accounting for the educational composition of migrants or opportunities to migrate to alternative destinations (e.g., Karemera et al., 2000; Volger and Rotte, 2000; Hatton and Williamson, 2002; Pedersen et al. Oguledo, 2004; Gallardo-Sejas et al., 2006; Clark, Hatton, and Williamson, 2007). One exception is Mayda (2005).

migrants is larger toward destinations with greater skill-related earnings differentials. We estimate the impact of income on migration with and without controlling for taxation in the destination. Post-tax income is the stronger predictor of migration, suggesting that migrants consider the tax treatment of earnings in choosing their destination.

We also present evidence on the role of other factors that influence migration, such as language, geographic proximity, and historical relationships. The relative stock of more-educated migrants is larger between source-destination pairs that share a common language, lack a common border, are located on different continents, or have never been in a colonial relationship. Greater linguistic and geographic distance make migrants less skilled. Visa and migration policies matter for migrant skill, with destination countries that favor asylees and refugees in their admission decisions receiving less-educated migrants.

Finally, we analyze the distribution of immigrant skills among destination countries. The factors included in our regression model explain a substantial share of the heterogeneity across destinations in average immigrant skills. Income differences play by far the most important role.

2. Theory and Empirical Specification

Consider migration flows between many source countries and many destination countries, which we model as a function of the net income gain from emigrating. Let the wage for individual i from source country s in destination country h be

$$(1) \quad W_{ish} = e^{\mu_h + \delta_h Z_{is}},$$

where μ_h is the return to uneducated labor in destination h , δ_h is the return to schooling in h , and z_{is} is the education level of individual i .⁶ Migration costs have observed and unobserved components, such that for individual i from source country s the cost of migrating to destination country h is

$$(2) \quad C_{ish} = g(z_{is}, x_{sh}) + \pi_{sh} + \varepsilon_{ish}.$$

The function $g(z_{is}, x_{sh})$ captures migration costs that depend on both characteristics of the source-destination pair x_{sh} and an individual's education level z_{is} . Characteristics of source-destination pairs include linguistic and geographic distance and destination-country immigration policies that are specific to particular source countries. The effects of such characteristics may depend on the migrant's skill due to time costs associated with migration or due to skill-specific immigration policies in h . There are two unobserved components of migration costs: π_{sh} , which is specific to the source-destination pair (and which subsumes x_{sh}), and ε_{ish} , which is idiosyncratic. We assume the utility associated with migrating from country s to country h is a linear function of wages and migration costs, given by

$$(3) \quad U_{ish} = W_{ish} - C_{ish} = e^{\mu_h + \delta_h z_i} - g(z_{is}, x_{sh}) - \pi_{sh} - \varepsilon_{ish}.$$

The utility from not migrating is assumed to equal the source country wage.

If idiosyncratic migration costs are correlated across destination countries and have an extreme value distribution, then the model has a nested-logit structure, with individuals first choosing whether or not to migrate and migrants then choosing among destination countries. Borrowing from the logit specification in Berry (1994), suppose that these idiosyncratic costs are given by,

⁶ In (1), we do not allow for unobserved components of skill that may affect wages, which are of central concern in Borjas (1987, 1991).

$$(4) \quad \varepsilon_{ish} = \kappa_{is} + (1 - \sigma)v_{ish},$$

where κ_{is} is a random component of migration costs common to all destinations (e.g., the idiosyncratic component of the psychic cost of leaving home), v_{ish} is a random component of costs specific to destination h , σ is the correlation in the v_{ish} 's across destinations (with $0 \leq \sigma < 1$), and $\kappa_{is} + (1 - \sigma)v_{ish}$ has an extreme value distribution.⁷ Where σ is close to one, there is little idiosyncratic variation in the decision over destination countries. The sorting of migrants across destinations will be dominated by differences in wages and observed migration costs, making migration flows lumpy. Most labor from a given source country will flow to whichever destination has the highest net return to migration based on observables. In contrast, where σ is close to zero, the cross-individual, cross-destination-country variation in idiosyncratic migration costs will allow migrants from a given source country to flow to multiple destinations.

In the data, we observe three levels of education: primary, secondary, or tertiary schooling. Define $\exp(\mu_h)$ to be the base wage, or wage paid to primary labor, in country h ; δ_h^2 to be the return to secondary education; and δ_h^3 to be the return to tertiary education. We assume variable migration costs are a linear function of variables that characterize source-destination pairs, whose impact on costs may vary with skill. Putting this assumption together with equations (3) and (4), the utility to individual i in education group j from migrating to country h is then

$$(5) \quad U_{ish}^j = e^{\mu_h + \delta_h^j} - \theta^j x_{sh} - \pi_{sh} - \kappa_{is} - (1 - \sigma)v_{ish}.$$

⁷ In this specification of random migration costs, the location options facing an individual consist of two groups. Group one has as its only option the source country; group two consists of all other locations (which could be organized into two or more subgroups if the migration decision tree has more than two branches). For each individual, κ is common to all locations and has a distribution that depends on σ , with $0 \leq \sigma < 1$. In particular, κ has the property that if v is extreme value then so is $\kappa + (1 - \sigma)v$, with σ capturing the correlation in migration costs across non-source country locations.

Given the extreme value distribution on the idiosyncratic error in (5) and the assumption that the coefficients $(\mu_h, \delta_h^j, \theta^j)$ are constant across individuals, we can apply results in Berry (1994) to write the log odds of migrating to destination country h versus staying in the source country (for education group j in source country s) as,

$$(6) \quad \ln \frac{E_{sh}^j}{E_s^j} = (W_h^j - W_s^j) - \theta^j x_{sh} - \pi_{sh} + \sigma \ln E_{sh/H}^j + \eta_{sh}^j,$$

where E_{sh}^j is the share of education group j in s that migrates to h , E_s^j is the share of education group j in s that remains in s , $W_h^j = e^{\mu_h + \delta_h^j}$, $E_{sh/H}^j$ is the fraction of those in group j who migrate from s that choose destination h (the within-group migration share), and η_{sh}^j is a disturbance term associated with measurement error in migration flows.

To eliminate fixed migration costs from (6), we take the difference between the log odds of migrating to h for tertiary and primary education groups:

$$(7) \quad \ln \frac{E_{sh}^3}{E_s^3} - \ln \frac{E_{sh}^1}{E_s^1} = (W_h^3 - W_s^3) - (W_h^1 - W_s^1) - (\theta^3 - \theta^1) x_{sh} + \sigma \ln \frac{E_{sh/H}^3}{E_{sh/H}^1} + (\eta_{sh}^3 - \eta_{sh}^1).$$

To control for the source country wage and within group shares, we need simply introduce source-country dummies into (7). To see why, rewrite (7) as

$$(8) \quad \ln \frac{E_{sh}^3}{E_{sh}^1} = \frac{1}{1 - \sigma} \left((W_h^3 - W_s^3) - (W_h^1 - W_s^1) - (\theta^3 - \theta^1) x_{sh} + \ln \frac{E_s^3}{E_s^1} - \sigma \ln \frac{E_{sH}^3}{E_{sH}^1} + (\eta_{sh}^3 - \eta_{sh}^1) \right)$$

where $\ln E_{sH}^j$ is the share of education group j in country s that migrates to any country.

Equation (8) then reduces to

$$(9) \quad \ln \frac{E_{sh}^3}{E_{sh}^1} = \beta_0 + \beta_1 x_{sh} + \beta_2 (W_h^3 - W_h^1) + \alpha_s + \tilde{\eta}_{sh},$$

where $\beta_1 = (\theta^1 - \theta^3)/(1 - \sigma)$, $\beta_2 = 1/(1 - \sigma)$, $\tilde{\eta}_{sh} = (\eta_{sh}^1 - \eta_{sh}^3)/(1 - \sigma)$, and the source country fixed effect is $\alpha_s = \left[\ln E_s^3 / E_s^1 - \sigma \ln E_{sH}^3 / E_{sH}^1 - (W_s^3 - W_s^1) \right] / [1 - \sigma]$. We refer to equation (9) as the sorting regression.

The dependent variable in equation (9) is the log skill ratio, where the skill ratio is the number of skilled migrants from s to h relative to the number of unskilled migrants. The second variable on the right of (9) is the destination-country wage difference; that is, the difference between wages paid to skilled labor and the wages paid to unskilled labor in destination country h . Income maximization implies that its coefficient, β_2 , should be positive. The positive coefficient implies positive sorting: if the wage difference in destination h exceeds the wage difference in destination k , then destination h will receive a more skilled mix of emigrants from source s than will destination k , all else equal.⁸

The specification in (9), while quite simple, is robust to arbitrary sources of fixed migration costs and to variation across source countries in the average attractiveness of migrating abroad. Migration flows between a given source and destination country will be affected by the other destination-country options that are available, much in the way that the national import price index affects bilateral commodity flows in the gravity model of trade (Anderson and Van Wincoop, 2004). Because the source-country fixed effect in (9) subsumes the overall share of emigrants in the population (measured in

⁸ The sorting regression is partial equilibrium in nature and cannot be used to examine how bilateral migration flows affect the wage structure in destination countries. An implicit assumption of our analysis is that during the sample period labor flows are insufficient to change the ranking of destination countries in terms of their attractiveness to more and less-educated labor.

relative terms for the skilled and unskilled by E^3_{sh}/E^1_{sh}), it controls for the mean emigration propensity. Thus, we can use the sorting regression to evaluate bilateral migration flows without having data on the universe of destination countries.⁹

The specification we derive differs from Borjas (1987) in that we explicitly allow for migration costs that are fixed in monetary units and abstract away from the role of unobserved characteristics in migrant selection. By introducing fixed costs, the sorting of migrants across destinations depends on *level* differences in wages, rather than *relative* differences. Other analysts have studied migrant sorting across multiple destination regions. Borjas, Bronars, and Trejo (1994) develop a model that predicts sorting on the basis of destination returns to skill, whereas our model predicts sorting on the basis of destination wage differences. Dahl (2002) estimates a reduced-form model of sorting. Using data for a single destination (in which, obviously, one cannot examine sorting), Rosenzweig (2007) derives a migration regression based on Roy (1951). The contribution of our work is to show that, subject to some assumptions on wages and migration costs, sorting on the basis of destination-country wage differences is a direct implication of income maximization.

Our emphasis on level differences in income is similar to Rosenzweig (2007). In his treatment of migrant selection, however, he assumes that the return to schooling is constant across destination countries, such that in equation (1) we would have

$W_h^j = e^{\mu_h + \delta^j}$. In this case, the incentive to migrate would be driven entirely by variation

⁹ The specification of the disturbance in equation (4) embodies the assumption that IIA applies among destination countries. In the empirical analysis, the sample of destination countries is limited to OECD members. To estimate (9), we need only that IIA applies to the OECD countries in the sample. Because we control for source-country fixed effects, the analysis is consistent with more complicated nested structures, in which we examine only the OECD branch of the decision tree. (One such structure would be one in which individuals first choose to migrate or not migrate, migrants then choose either OECD or non-OECD sets of destination countries, and sub-migrants then choose among destinations within these sets.)

in the destination-country base wage, since $W_h^3 - W_h^1 = e^{\mu_h} (e^{\delta^3} - 1)$. To see if migrant sorting depends on variation in both the base wage and the return to skill, write (9) as

$$(10) \quad \ln \frac{E_{sh}^3}{E_{sh}^1} = \beta_0 + \beta_1 x_{sh} + \beta_2 W_h^1 \left(\frac{\overline{W^3}}{W^1} - 1 \right) + \beta_3 W_h^1 \left(\frac{W_h^3}{W_h^1} - \frac{\overline{W^3}}{W^1} \right) + \alpha_s + \tilde{\eta}_{sh},$$

where $\frac{\overline{W^3}}{W^1}$ is the mean ratio of high-skill to low-skill wages across destinations. The term that multiplies β_2 is a scaled version of the destination base wage. The term that multiplies β_3 is what we refer to as the skill markup: it is the base wage times the relative markup to skilled labor in destination h . Based on equation (10), the Rosenzweig assumption on constant skill returns implies that the coefficient estimate for β_3 should equal zero.¹⁰ To test this prediction, we report an estimate of equation (10) in section 4.2.

3. Data and Empirical Setting

To examine international migration, we take data from Docquier and Marfouk (2006; hereafter, DM) on stocks of emigrants by source and destination country.¹¹ In collaboration with the national statistical offices of the 30 OECD countries, they have estimated the population in each OECD country of immigrants 25 years and older by

¹⁰ To see this, note that $\frac{W_h^3}{W_h^1} - \frac{\overline{W^3}}{W^1} = e^{\delta^3} - e^{\delta^3} = 0$.

¹¹ Until recently, there were no data on the population of migrants by source and destination region for more than a handful of countries. Early attempts to construct cross-country data include Carrington and Detragiache (1998), who estimate the stock of migrants with tertiary education from 61 source countries residing in OECD countries; Adams (2003), who estimates emigration rates for 24 labor-exporting countries; and the OECD (2003), which estimates the foreign-born population 15 years and older in 2000 by source country and broad education level for each OECD member country (the usefulness of the OECD data is limited by the fact that a large share of migrants in the data have unknown education levels).

source country and education level. In some of the OECD destination countries, these counts are based on census data, whereas in others they are based on register data. Because education systems differ so much among countries, it is nearly impossible to categorize educational attainment in a comparable manner at a fine level of detail. To enhance comparability, DM classify schooling levels into broad three categories: primary (0-8 years), secondary (9-12 years), and tertiary (13 plus years).

In this section, we describe patterns of international migration into OECD countries based on the DM data. The original version of DM groups destination countries into three regions: North America, Europe, and Australia & Oceania. The descriptive statistics in Tables 1 and 2 are based on these data. For the regression analysis reported in section 4, we use an extended version of the DM data, compiled by Beine, Docquier, and Rapoport (2006b; hereafter BDR), which provides immigrant counts in 2000 by source country for 20 individual OECD countries.¹²

3.1 Measurement of Emigrant Stocks

Not surprisingly, aggregating data from multiple destination countries raises several comparability issues. The first involves the definition of immigrants. Some countries, such as Germany, define immigrants on the basis of country of citizenship rather than country of birth. This causes some of the foreign born to be excluded from

¹² The universe of destination countries in the DM data is the 30 OECD members as of 2000. Our set of 20 destination countries (Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the US, the UK) excludes very small OECD members (Iceland, Luxembourg), OECD members who are largely closed to immigration (South Korea, Japan), and recently joined OECD members (the Czech Republic, Hungary, Mexico, Poland, the Slovak Republic, Turkey) who are primarily labor exporters. These 20 countries account for 94.1% of the foreign-born population living in OECD countries.

DM's immigrant counts in these countries. In the regression analysis, we check the robustness of the results by dropping such countries from some of the specifications.

Measuring education levels poses several problems. In Belgium and Italy, the statistical office reports aggregate immigrant counts but does not disaggregate by education level. DM impute the skill distribution of immigrants in such cases using data from household labor-force surveys, but in light of the role that education plays in our analysis, we drop Belgium and Italy from the sample of destinations.

National statistical offices differ in how they classify educational attainment. Some countries' classification systems have no attainment category that distinguishes whether a person who lacks a secondary-school qualification (such as a high school diploma) acquired any secondary education, or whether their schooling stopped at the primary level (grade 8 or below). This could result in inconsistencies in the share of primary-educated immigrants across destination countries. We discuss the implications of this problem, and our approach to dealing with it, in section 4.2.

Some immigrants may have acquired their tertiary schooling in the destination country. By implication, they might have obtained less schooling had they not migrated. BDR provide some evidence on this point in the form of immigrant counts (for those with tertiary education) that vary by the age at which migrants arrived in the destination country (any age, 12 years or older, 18 years or older, 22 years or older). They find that 68% of tertiary migrants arrive in the destination country at age 22 or older, and 10% arrive between ages 18 and 21, suggesting the large majority of tertiary emigrants depart sending countries at an age at which they would typically have acquired at least some post-secondary education. Reassuringly, the correlations in emigration rates by age at

migration range from 0.97 to 0.99. In section 4.2 we provide additional checks on the importance of tertiary schooling acquired in the destination country.

Finally, although our theoretical framework treats migration as a permanent decision, many migrants do not remain abroad forever. There is considerable back-and-forth migration between neighboring countries (Durand, Massey, and Zenteno, 2001), which we address by controlling for source-destination proximity. Some migrants are students who will return to their home countries after completing their education. These migrants may have been motivated by educational opportunities in destination countries, as well as wage differences (Rosenzweig, 2006). The DM and BDR data partially address this issue by restricting the foreign born to be individuals 25 years and older, a population that should have largely completed its schooling. In 2000 in the United States, the share of foreign-born individuals 25-64 years old with tertiary education who stated they were in school was 13.6%. In section 4.2 we attempt to control for differences in educational opportunities between source and destination countries.

3.2 International Migration Patterns

Much of the research on international migration examines one end of the skill distribution or the other, with work on brain drain focusing on the high skilled and work on migrant selection focusing on the low skilled. Given the literature, the actual distribution of emigrants by schooling is more even than one might guess. Table 1 shows the share of emigrants by skill level and destination region. The bottom row shows that the emigrant skill distribution is almost uniform, with 35.5% of emigrants having a primary education and 35.3% having a tertiary education. The first column shows that

the distribution of emigrants across destination regions is much less even, with North America being by far and away the largest receiving region. In 2000, North America accounted for 51.4% of immigrants in OECD countries, Europe accounted for 38.4%, and Australia and Oceania accounted for 10.2%.

Also apparent in Table 1 is positive sorting of migrants across destinations. Relative to the other OECD regions, North America attracts a disproportionate share of skilled migrants. In 2000, 65.5% of emigrants with tertiary education chose North America, which, as we discuss below, has large skill-related wage differences, whereas 23.6% chose Europe, which has small skill-related wage differences. In contrast, among those with a primary education, 35.2% chose North America and 56.0% chose Europe. Such sorting is consistent with income maximization.

However, other factors, such as geography, may also affect migrant sorting. Table 2 shows the share of OECD immigrants by country of origin for the 15 largest source countries. One sees there that source countries tend to send emigrants to nearby destinations, as is apparent in Turkish migration to Europe, Korean migration to Australia and Oceania, and Mexican and Cuban migration to the United States. Yet, nearly all of the source countries in Table 2 send migrants to all three destination regions. As we show in the next section, a similar pattern holds in the BDR data on migration to individual OECD countries. This feature of the data is important, for it allows us to estimate the sorting regression controlling for source-country fixed effects. Absent migrant flows from each source country to multiple destinations (which obtains for all but very small source countries), our estimation strategy would be infeasible.

3.3 Destination-Country Income Measures

The key explanatory variable in our regression model is the destination-country difference in wages between more and less-skilled workers. Ideally, we would estimate wages by broad education category from the same sources used by DM. Since such data are not available to us, we turn to a different source and a different construct of skill-related wage differences.

A natural data source is the Luxembourg Income Study (LIS), which collects microdata from the household surveys of 30 primarily developed countries worldwide. This includes most of the destination countries in the BDR data, with the exceptions of Finland, Greece, New Zealand, and Portugal. The intersection of the 12 countries for which BDR and LIS provide useful data (Australia, Austria, Canada, Denmark, France, Germany, the Netherlands, Norway, Spain, Sweden, the UK, the US) were host to 91 percent of immigrants in the OECD in 2000.¹³ We use data from waves 4 and 5 of the LIS, which span the years 1994-2000.¹⁴

An appealing feature of the LIS is its efforts to enhance comparability of the data it receives from its contributor countries. It does this by extensively documenting the data and constructing variables based on common criteria where possible. Despite LIS's efforts to "harmonize" the survey data, however, a number of comparability issues arise.

¹³ In addition to Belgium and Italy, we exclude Switzerland from the destinations because the LIS provides no data on individual earnings for Switzerland after 1992. We also drop Ireland from the sample of destination countries because it receives immigrants from few source countries (although our regression estimates are similar when we include it). In 2000, Switzerland was host to 2.5 percent, and Ireland was host to 0.5 percent, of the foreign-born population residing in OECD countries.

¹⁴ The years corresponding to each country are as follows: Australia (1995, 2001), Austria (1994, 1995, 1997, 2000), Canada (1994, 1997, 1998, 2000), Denmark (1995, 2000), France (1994, 2000), Germany (1994, 2000), the Netherlands (1994, 1999), Norway (1995, 2000), Spain (1995, 2000), Sweden (1995, 2000), the UK (1994, 1995, 2000), and the US (1994, 1997, 2000).

One limitation of the LIS for our purposes is that its constituent household surveys sometimes classify educational attainment differently than the national statistical office of the corresponding country. This adds the problem of within-country comparability to the already difficult problem of between-country comparability. Ultimately, it proved impossible for us to map education categories between the BDR and the LIS data in a manner in which we had full confidence.

Instead of using education-specific earnings to measure skill-related wage differences, we used quantiles of each country's earnings distribution. We use the 20th percentile as our measure of low-skill wages and the 80th percentile as our measure of high-skill wages, averaging across the 1994-2000 period for each country in the LIS (see note 13). The key regressor in our model is represented by the 80-20 differential in earnings, familiar from studies of inequality.¹⁵

We also construct post-tax wage differences, since pre-tax wage differences overstate the return to skill enjoyed by workers and since tax policy varies within the OECD. Continental tax systems are more redistributive than tax systems in Anglo-Saxon countries (Alesina and Angeletos 2002). As a result, pre-tax wage differences may understate the relative income loss that skilled migrants would suffer in choosing Europe over one of the former English colonies.

To construct post-tax wage differences we employ average tax rates by income level published by the OECD since 1996 (OECD, various years). To 20th percentile earnings we apply the tax rate applicable to single workers with no dependents whose

¹⁵ In a previous version of this paper, we experimented with alternative measures of wage differences based on various measures of low-skill wages and different measures of the return to skill (the standard deviation of income, the ratio of income in the 80th to 20th percentiles, and the Gini coefficient). All of the alternatives we considered generated results similar to those we report in this paper.

earnings equal 67 percent of the average production worker's earnings. To 80th percentile earnings we apply the tax rate applicable to a comparable worker with earnings equal to 167 percent of the average production worker's earnings. In both cases, the tax rate includes income taxes net of benefits plus both sides of the payroll tax. Prior to averaging income across years, we match to each year and income group that year's corresponding tax rate.¹⁶ In section 4.2 we experiment with tax rates applicable to families with children as a means of dealing with the possible measurement error that arises from focusing on tax rates facing single workers.

Table 3 reports 20th and 80th percentile earnings and the 80-20 wage difference by destination, all in 2000 US dollars. Pre-tax data appear in columns (1) to (3) and post-tax data appear in columns (4) to (6). The average pre-tax wage difference is \$22,310, whereas the average post-tax wage difference is \$10,810. The difference reflects an average tax rate of about 36 percent on 20th percentile earnings, as compared to an average tax rate of about 44 percent on 80th percentile earnings. Taxes also change some countries' rankings within the distribution of wage differences. The pre-tax wage differences of Denmark, Norway, and the UK place them in a second tier below the US and well above the mean. After tax, however, Britain remains above the mean (and second to the US), but Norway falls and Denmark is below the mean. Panel B of Table 3 shows that the countries that we excluded from the sample due to data quality concerns come mostly from the low end of the wage-difference distribution.

3.4 Other Variables in the Regression Model

¹⁶ Since the tax data only go back to 1996, we use tax rates for that year to calculate post-tax income values in 1994 and 1995.

Differences in language between source and destination countries may be relatively important for more-educated workers, since communication and information processing are likely to be salient aspects of their occupations. We control for whether the source and destination country share a common official language based on data from CEPII (<http://www.cepii.fr/>). Similarly, English-speaking countries may attract skilled emigrants because English is a lingua franca and is commonly taught in school. English-speaking countries may also attract the more skilled because they have common-law traditions that provide relatively strong protection of property rights (Glaeser and Schleifer, 2002). In Table 3, Anglophone countries tend to have the largest wage differences. To avoid confounding destination-country skilled-unskilled wage differences with the attraction of being in an English-speaking country, we control for whether a destination-country has English as its primary language.

The sorting specification in (9) differences out barriers to migration that are common to all individuals from a particular destination, leaving only barriers that affect education groups differentially. Migration costs are likely to be increasing in distance between a source and destination country, with credit constraints making the financing of a trip more difficult for lower-income individuals. Relatedly, proximity may make illegal immigration less costly, thereby increasing the relative migration of less-educated individuals. We include as regressors great circle distance, the absolute difference in longitude, and an indicator for source-destination contiguity.

Migration networks may lower migration costs, benefiting lower-income individuals disproportionately. Networks may be stronger between countries that share a

common colonial heritage, for which we control using CEPII's indicators of whether a pair of countries have short or long colonial histories.

Destination countries impose a variety of conditions in deciding which immigrants to admit. Many of these conditions involve the education level of immigrants either explicitly or implicitly. One indicator of the skill bias in a country's admission policies is the fraction of visas it reserves for refugees and asylees. Less-educated individuals may be more likely to end up as refugees, making countries that favor refugees in their admissions likely to receive more less-educated immigrants. We control for the share of immigrant inflows composed of refugees and asylees averaged over the 1992-1999 period (OECD, 2005).¹⁷ The European signatories of the Schengen Agreement have committed to abolish all border barriers, including temporary migration restrictions, on participating countries. We control for whether a source-destination pair were both signatories of Schengen as of 1999.¹⁸ Similarly, some countries do not require visas for visitors from particular countries of origin, with the set of visa-waiver countries varying across destination countries. While visa waivers strictly affect only tourist and business travelers, they may indicate a source-country bias that also applies to other immigrant admissions. We control for whether a destination country grants a visa waiver to individuals from a source country as of 1999.

¹⁷ Countries also differ in the share of visas that they reserve for skilled labor. Unfortunately, we could only obtain this measure for a subset of destination countries. Over time, the share of visas awarded to asylees/refugees and the share awarded to skill workers are strongly negative correlated (OECD, 2005), suggesting policies on asylees/refugees may be a sufficient statistic for a country's immigration priorities.

¹⁸ The years in which countries signed the Schengen Agreement are 1985 (Belgium, France, West Germany, Luxembourg, Netherlands), 1990 (East Germany, Italy), 1992 (Portugal, Spain, Greece), 1995 (Austria), 1996 (Denmark, Finland, Iceland, Norway, Sweden), 2000 (Ireland, United Kingdom), 2004 (Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia), 2005 (Switzerland), and 2007 (Bulgaria, Romania). We exclude all signatories in 2000 or later from classifying as Schengen participants.

4. Regression Analysis

4.1 Main results

Our main regression analysis is based on the specification shown in equation (9). The unit of observation is the source-destination country pair.¹⁹ The dependent variable is the log skill ratio, where the skill ratio is the number of tertiary-educated emigrants to the number of primary-educated emigrants who migrate from the source country to the destination country. Because the dependent variable has a log-odds metric, the magnitude of the regression coefficients does not have a particularly useful interpretation.²⁰ As a result, we focus in this section on the signs and significance levels of the coefficients. Regression results are reported in Table 4. In addition to the variables shown, all regressions include a full set of source-country dummies. The standard errors, reported in parentheses, are clustered by destination country.

Columns (1) and (2) report results from a specification that includes only the destination-country wage difference and the source-country dummies. The wage difference in column (1) is pre-tax, whereas the wage difference in column (2) is post-tax. Both wage difference coefficients are positive and significant. Controlling for source country, destination countries with larger skill-related wage differences receive immigrants with higher skill. That is, we see sorting across the 12 destination countries much like the sorting we observed across the three destination regions in Table 1. Such positive sorting is consistent with the prediction from our income-maximization model.

¹⁹ There are 12 destinations and 192 source countries. Since most source countries do not send emigrants to every destination country, the number of observations is less than $12 \times 192 = 2304$.

²⁰ Based on equation (9), one might think that the coefficient on the earnings difference would identify σ . However, this would only be true if the marginal utility of income is unity.

Although the regressions in columns (1) and (2) implicitly control for source-country incomes and source-destination migration costs common to all emigrants, there are clearly many other factors which could affect the economic sorting of emigrants according to skill. The specifications reported in columns (3) and (4) add a number of such factors to the model. These variables reflect geographic, linguistic, social, and political relationships between source and destination countries. Adding them to the regression reduces the magnitude of the wage-difference coefficients, but they remain positive and significant.

The coefficient on the dummy variable indicating whether the destination country is Anglophone is positive but significant only in column (3), which includes the pre-tax wage difference. The precision with which this coefficient is measured is influenced by collinearity between the English dummy and the wage difference. Nevertheless, it has a sensible interpretation. It indicates that English-speaking economies attract higher-skilled immigrants on average, all else equal, implying that English conveys an advantage to such countries in a world where English has emerged as the lingua franca spoken by educated people worldwide. Alternatively, higher-skilled migrants may be attracted to countries that have a legal tradition grounded in common law.

The next variable is also language-related, indicating whether the source and destination countries have an official language in common. Its coefficient is positive and significant, showing that the immigrant skill mix is higher among source-destination pairs that share the same official language. In terms of income maximization, it can be interpreted as showing that the cost of migrating to a foreign linguistic environment is greater for

high-skilled than for low-skilled workers. Presumably, this happens because high-skilled jobs are more demanding in the way of language skills than are low-skilled jobs.

The next three variables capture differences in geography between the source and destination countries. The coefficient on log distance is small and statistically insignificant. The next coefficient shows that migration between contiguous countries involves substantially more less-skilled migrants, all else equal, than migration between non-contiguous countries. In terms of the model, this suggests that contiguity provides a greater cost advantage for low-skilled migrants than for high-skilled migrants. The next coefficient shows the effect of longitude differences. Large differences in longitude generally imply that two countries lie across an ocean from each other. Thus, the positive coefficient suggests that trans-oceanic migration is more costly for low-skilled than for high-skilled migrants.

The next two variables capture the effects of historical colonial relationships. Both long-term relationships (e.g., the United Kingdom and India) and short-term relationships (e.g., the United States and the Philippines) are associated with lower-skill migration. Recent literature suggests that economic and social networks between industrialized countries and their former colonies contribute to bilateral migration flows, much in the way such networks also appear to contribute to bilateral trade (Pedersen, Pytlikova, and Smith 2004, Mayda 2005). Our empirical results are consistent with these linkages disproportionately affecting migration of the less-skilled.

The next three variables capture aspects of immigration policy. The visa waiver variable is a dummy equal to one if the source and destination country have a treaty in place that relaxes visa requirements citizens of the source country in traveling to the

destination country. The Schengen signatory variable is a dummy equal to one if both the source and destination country signed the Schengen treaty before 2000. Although only the Schengen coefficients are significant, all coefficients are positive, indicating that the relaxation of travel restrictions results in relatively more skilled immigration. The other immigration policy measure in columns (3) and (4) is the share of residency visas granted to asylum seekers by the destination country. The regression coefficient shows that a higher share of asylum seekers substantially reduces the immigrant skill levels.

4.2 Robustness Checks

Table 5 reports results from a number of specifications designed to check the robustness of our results. Since the post-tax wage differences are more significant and have more explanatory power than the pre-tax wage differences in Table 4, we focus on the post-tax measures for the remainder of the analysis. Furthermore, all of the estimates reported below are taken from regressions that include source-country dummies and all the variables reported in our baseline specification, reported in column (4) of Table 4. Here we present only the wage difference coefficients in order to conserve space.

For convenience, the first column of Table 5 reports our baseline estimate. The estimates in columns (2) and (3) are based on PPP-adjusted wage differences. The wage difference in column (2) adjusts for PPP in the destination country, which would be the relevant adjustment if destination-country earnings were intended solely to finance destination-country consumption. The measure in column (3) adjusts for PPP in the source country, which would be the relevant adjustment if destination-country earnings were intended solely to finance source-country consumption, possibly by way of remittances. With either adjustment, the wage-difference coefficient remains positive

and significant. The coefficient in column (3) is only about one-fourth the magnitude of the baseline coefficient, but much of the difference is a matter of scaling, since wage differences adjusted for source-country PPP are roughly three times higher than the unadjusted wage differences.

Column (4) reports results from a specification designed to test whether the positive effect of the wage difference on immigrant skill is due to variation in base wages or variation in returns to skill. Here we have decomposed the (unadjusted) wage difference into the two parts shown in equation (10): the base wage (scaled by the mean

return to skill across destination, (i.e., $W_h^1 \left(\frac{\overline{W^3}}{W^1} - 1 \right)$), and the skill markup

(i.e., $W_h^1 \left(\frac{W_h^3}{W_h^1} - \frac{\overline{W^3}}{W^1} \right)$). Both coefficients are positive, but only the skill-markup

coefficient is significant. This suggests that higher-skilled immigrants are primarily attracted by higher skill premia, rather than higher base wages, contrary to the assumption in Rosenzweig (2007).

In Table 6 we return to our original unadjusted wage difference measure but report results obtained from different samples and specifications that are designed to address some of the data problems discussed in section 3. Column (1) repeats our baseline estimate from column (4) of Table 4. In column (2) we drop observations involving Germany as a destination country. Among the destinations countries in our sample, Germany is the only one where immigration is defined for census purposes in terms of citizenship rather than place of birth. This distinction has no effect on our results, since the estimate in column (2) is nearly the same as the baseline estimate.

In column (3) we deal with the inconsistent classifications of primary education across different destination countries. As noted above, some countries' national statistical offices provide explicit codes for primary education levels, whereas others do not, indicating instead only whether the respondent acquired a secondary-school qualification. In these cases, BDR appear to allocate those without secondary qualifications to the primary category.²¹ The problem is that many such persons would have received at least some secondary schooling. Thus two destination countries with the same true distribution of immigrant education could have different skill shares in the BDR data depending on how their statistical office coded education, with the country lacking the primary category showing the higher share of primary-schooled immigrants by BDR's definition and therefore the lower skill share.

To deal with this issue we obtained census documentation and information about the education systems for nine of our 12 destination countries. We then constructed two dummy variables, one equal to one if the destination-country statistical office codes a primary education category (Austria, Australia, France, Spain, and the US), and another equal to one for the four countries for which we were unable to locate documentation (Denmark, Netherlands, Norway, and Sweden). We included these dummies in our regression; the base group consists of countries that do not explicitly code primary education (Canada, Germany, and the United Kingdom).

²¹ This is true at least for Canada, which lacks a primary-education category and whose immigrant education distribution we were able to match to BDR's using the Statistics Canada web-based Census tabulation program

(<http://www12.statcan.ca/english/census01/products/standard/themes/RetrieveProductTable.cfm?Temporal=2001&PID=68534&METH=1&APATH=0&PTYPE=55496&THEME=43&FREE=0&AID=0&FOCUS=0&VID=0&GC=0&GK=0&SC=1&CPP=99&SR=1&RL=0&RPP=9999&D1=0&D2=0&D3=0&D4=0&D5=0&D6=0&GID=517770>).

Column (3) reports the wage-difference coefficient from the regression that includes the two coding-scheme dummies. The coefficient is smaller when we account for differences in educational coding schemes. However, it remains positive and statistically significant. The coefficients on the coding-scheme dummies were both positive and significant, indicating that the coding schemes indeed affect immigrant skill ratios in the expected manner (and that the four countries whose documentation we could not locate probably code a primary education category).

Column (4) addresses the problem that some emigrants may have obtained their tertiary education in the destination country rather than the source country. If the cost of acquiring tertiary education across destination countries were negatively correlated with destination-country wage differences, then the effect on immigrant skill that we attribute to wage differences could instead be due to differences in educational costs. To deal with this issue we redefine the numerator of the skill share to be the sum of tertiary- and secondary-educated immigrants. This addresses the problem if we can assume that all tertiary-educated immigrants would have obtained at least a secondary education in their source country. The coefficient in column (4), which is based on this alternative definition of the log skill share, is positive and significant, suggesting that the effect which we interpret as migrant sorting is not entirely attributable to differences in the costs of tertiary education across destination countries.

The results in columns (5) and (6) are based on samples that let us assess the influence of source-destination cells with very small shares of primary-educated migrants. In column (5) we drop cells where fewer than 3 percent of migrants were primary-educated; in column (6) we employ a 5-percent threshold. In both cases the

wage-difference coefficient is smaller than the baseline estimate, but the estimates remain positive and significant.

The final column reports an instrumental variables estimate based on an alternative set of post-tax wage differences. Whereas our main wage difference is based on tax rates faced by taxpayers without dependents, many taxpayers in fact have dependents. Since families with dependents enjoy tax benefits in many countries, this means that our post-tax wage differences may be measured with error. As a check, we constructed an alternative set of post-tax wage differences based on tax rates faced by taxpayers with dependents and used this alternative measure as an instrumental variable. The coefficient in column (7) is greater than that in column (1), consistent with measurement error, but the difference is so slight as to be inconsequential.

Table 7 reports the results of adding to our baseline specification a number of variables designed to capture other potential costs or benefits of migration that may vary by skill level. Column (1) reiterates our baseline estimate. Column (2) adds a relative university quality measure. It is equal to the average rank of universities within the destination country (among top 250 universities worldwide), interacted with a dummy variable equal to one if the source country has no ranked universities. We intend this as a proxy for the education-related benefit of migrating relative to remaining in the home country. The coefficient is negative as one might expect (higher-ranked institutions have ranks closer to one) and significant. Higher ranked universities appear to act as a draw for higher-skilled immigrants from countries with low-quality education systems. At the same time, the wage difference coefficient remains positive and significant.

Column (3) adds a dummy variable equal to one if the destination country has a military base in the source country with at least 1000 troops. Such bases could lower migration costs for source-country workers employed on base or increase the familiarity of the destination to residents of the source country. The coefficient is positive but dwarfed by its standard error.

Column (4) adds a measure of the latitude difference between the source and destination and column (5) adds a dummy equal to one if the countries share a minor (i.e., not official) language in common. Lower distances and common languages could conceivably lower migration costs in a manner that differed by skill. However, neither coefficient is significant.

5. Explaining Differences in Immigrant Skills across Destinations

Our regression results are largely consistent with the predictions from our income maximization model: the higher the destination-country wage difference for skilled workers, the more-skilled immigrants the destination attracts, holding the source country constant. This main result holds up and is statistically significant across a variety of specifications. At the same time, the log-odds metric of our skill measure makes the regression coefficients difficult to interpret in a useful way. In this section we attempt to provide a quantitative interpretation for our results. Although there are different ways one might proceed, we focus on a natural question: to what extent do our estimates, and particularly the destination-country wage differences, explain differences in mean immigrant skills among the destination countries?

Before discussing the details of our approach, it is useful to look first at mean levels of immigrant skill by destination. Table 8 presents three such measures: the mean

log skill ratio in column (1), the mean share of immigrants with tertiary schooling in column (2), and the mean share of immigrants with primary schooling (an inverse measure of immigrant skill) in column (3). Based on the mean log skill ratio, which is the skill measure motivated by our theory and explained by our regression models, the US has the most highly skilled immigrants on average, followed by Canada and Australia. We seek to explain the immigrant skill gap, defined as the difference between the mean log skill ratio among immigrants in the United States and the mean log skill ratio among immigrants in other destination countries. The immigrant skill gap is reported in column (4).

For the most part, destinations with high log skill ratios, and therefore low immigrant skill gaps, also rank highly on other measures of immigrant skill, such as the share with tertiary education or the inverse of the share with primary education. An exception involves the United States, which ranks first in log skill ratios, and Canada, which ranks first in the share with tertiary education. The reason for the difference can be seen in column (3): the US has a lower share of primary-educated immigrants than Canada. It is impossible to tell whether this is truly because the US has relatively fewer primary-educated immigrants than Canada, or whether it stems from the fact that Canadian census data do not distinguish someone with a primary education from someone with a secondary education but no secondary qualification. This clearly affects the interpretation of our immigrant skill decomposition as between particular pairs of destination countries. At the same time, regardless whether we focus on the log skill ratio or the share with tertiary education, the same groups of countries appear at the

extremes of the immigrant skill distribution: the former English colonies appear near the top, and central and northern European countries appear near the bottom.

To assess which factors explain the immigrant skill gap, we first adopt a more compact notation for equation (9), letting $y_{sh} = \ln(E_{sh}^3 / E_{sh}^1)$ and $W_h = W_h^3 - W_h^1$, so equation (9) can be rewritten as,

$$y_{sh} = \beta_0 + \beta_1 x_{sh} + \beta_2 W_h + \alpha_s + \tilde{\eta}_{sh}.$$

The properties of OLS regression estimates let us write each destination country's mean log skill share as

$$\bar{y}_h = \hat{\beta}_0 + \hat{\beta}_1 \bar{x}_h + \hat{\beta}_2 \bar{W}_h + \bar{\alpha} + \hat{\eta}_h,$$

where overbars define averages over source countries and hats denote OLS estimates.

Differencing between the mean log skill ratio of the US and that of the hth destination country yields the immigrant skill gap

$$(11) \quad \bar{y}_{US} - \bar{y}_h = \hat{\beta}_1 (\bar{x}_{US} - \bar{x}_h) + \hat{\beta}_2 (\bar{W}_{US} - \bar{W}_h) + \hat{\eta}_{US} - \hat{\eta}_h.$$

Each term on the right hand side of equation (11) tells us how much of country h's immigrant skill gap can be explained by the corresponding variable; each term is the product of the corresponding regression coefficient and the difference between the mean value of the variable in the US and the mean value of the variable in the hth destination. To aid interpretation, we divide each term by the value on the left hand side of equation (11), showing the share of the immigrant skill gap explained by each variable in the regression.

Results are given in Table 9. The first column shows that the wage difference explains a substantial share of the immigrant skill gap. In all cases the share explained by

the wage difference exceeds 40 percent. In countries with relatively small immigrant skill gaps, such as Australia and Canada, it exceeds 100 percent.²²

The next two columns show the importance of language. English explains at least 12 percent of the immigrant skill gap for each non-Anglophone destination country. The role of common languages is smaller overall, but nevertheless fairly important for some of those destination countries whose languages are not widely spoken elsewhere.

The next three columns quantify the importance of distance. Most of the entries in the log distance column are zero, owing to the insignificant coefficient on log distance in the regression. Contiguity has little effect, but longitudinal differences, representing the extent to which reaching the destination country involves crossing an ocean, explains an important share of immigrant skill gaps. The negative entry for Australia indicates that its geographic isolation from potential immigrant-sending regions helps to explain why its immigrant skill gap is fairly small. That is, based on the other factors in the regression model, its skill gap would be 15 percent greater were it not for its isolated location. In contrast, the geographic proximity of Europe to Africa, the Middle East, and western Asia explains roughly 10 to 20 percent of European immigrant skill gaps.

Visa waivers and the Schengen treaty explain relatively little of the immigrant wage gap. Asylum policy, in contrast, has important effects. In half of the destination countries in our sample, asylum policy explains at least 10 percent of the immigrant skill disadvantage. In the Netherlands it explains nearly a third of the skill gap.

One interesting question that can be addressed with Table 9 (and Table 8) is, Why do the UK's immigrants more closely resemble those in Europe than those in the other

²² Since the last term in (11) is the difference in mean residuals, each row in Table 10 adds to 1. However, nothing constrains the share explained by any subset of components to be less than one.

Anglophone economies? One obvious answer is its wage structure: if the UK's base wage difference were equal to that of the US, its immigrant skills gap would be 43 percent smaller. Yet, Britain's combination of history, geography, and immigration policy play a role, too. Together, its location on the prime meridian and the extent of its former empire explain 28 percent of its immigrant skills gap. Its asylum share explains another 13 percent. With a 41-percent smaller immigrant skills gap, Britain's mean immigrant skill ratio would rise to 1.02, making it look more Anglo-Saxon and less European (see Table 9).²³

Since the total share explained, including residual differences, sums to one, one cannot gauge the overall fit of the model by inspecting the total or the residuals. A more meaningful measure of the extent to which the model explains immigrant skill differences between destinations is the share of the between-destination variance in the immigrant skill gap that is explained by the model. The share explained by the regressors is 82 percent, indicating that the combination of economic, linguistic, geographic, and policy variables included in the model account for much of the difference in immigrant skills that exist among destination countries.

6. Conclusions

Recent data show that emigrants to the OECD are almost universally better educated, on average, than their countrymen who choose not to emigrate. This runs counter to the negative selection that is predicted by income maximization when source-country returns to skill exceed destination-country returns to skill and migration costs are fixed in terms of time. When migration costs are fixed in monetary terms, income

²³ $1.02 = 0.39 + .41 (1.54)$

maximization is consistent with either positive or negative selection; we show that with fixed monetary costs, income maximization implies that emigrants should sort themselves according to skill such that destinations with the largest rewards to skill receive the most highly skilled immigrants, all else equal.

We test for sorting using data on emigrants from 192 source countries to a dozen OECD destinations. Our results are consistent with the theory. Other important determinants of migration patterns include language, geography, and visa policy. Destination countries with more lenient asylum policies receive less-skilled immigrants, all else equal, than those with more restrictive policies. Economic, linguistic, and policy factors explain an important share of the variation in immigrant skills among destination countries, but the potential wage gains across destinations matter most of all.

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Figure 1: Share of emigrants and general population with tertiary education, 2000

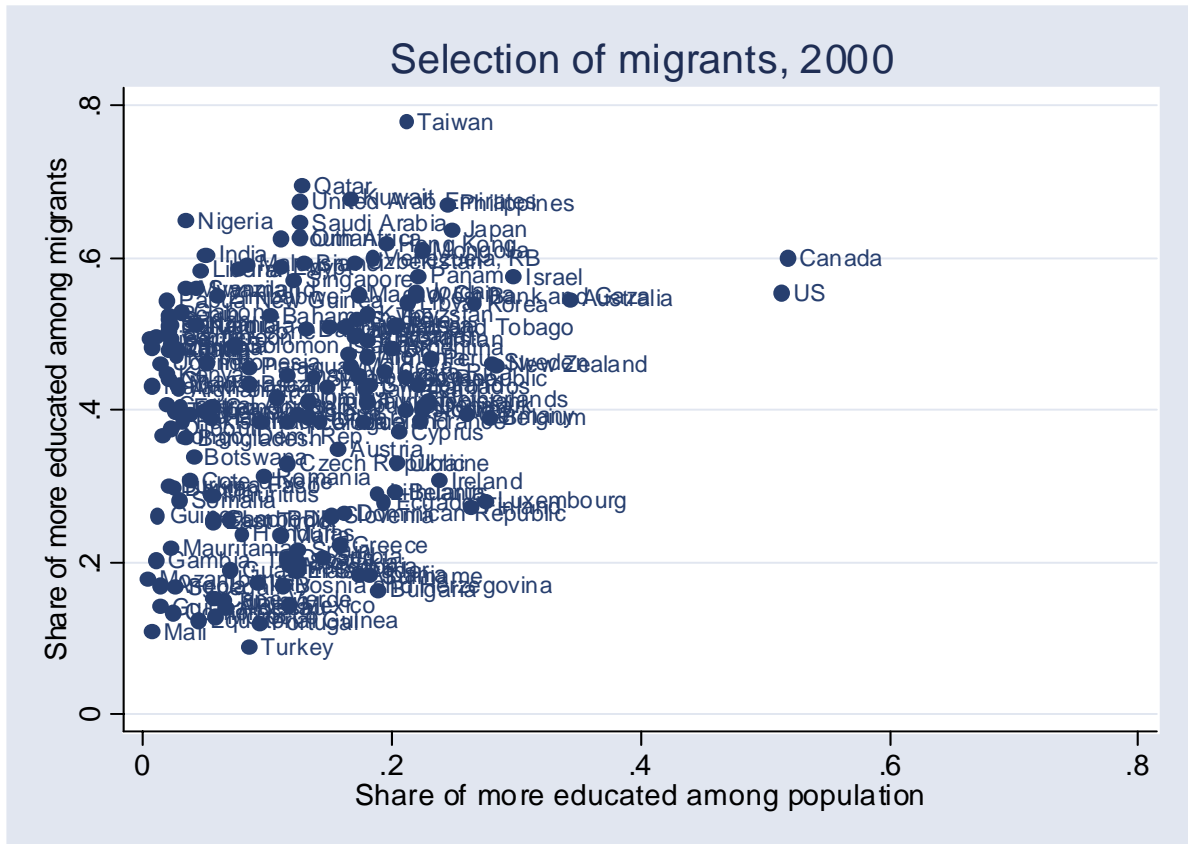


Figure 2: Emigration odds (primary and tertiary educated) by source country, 2000

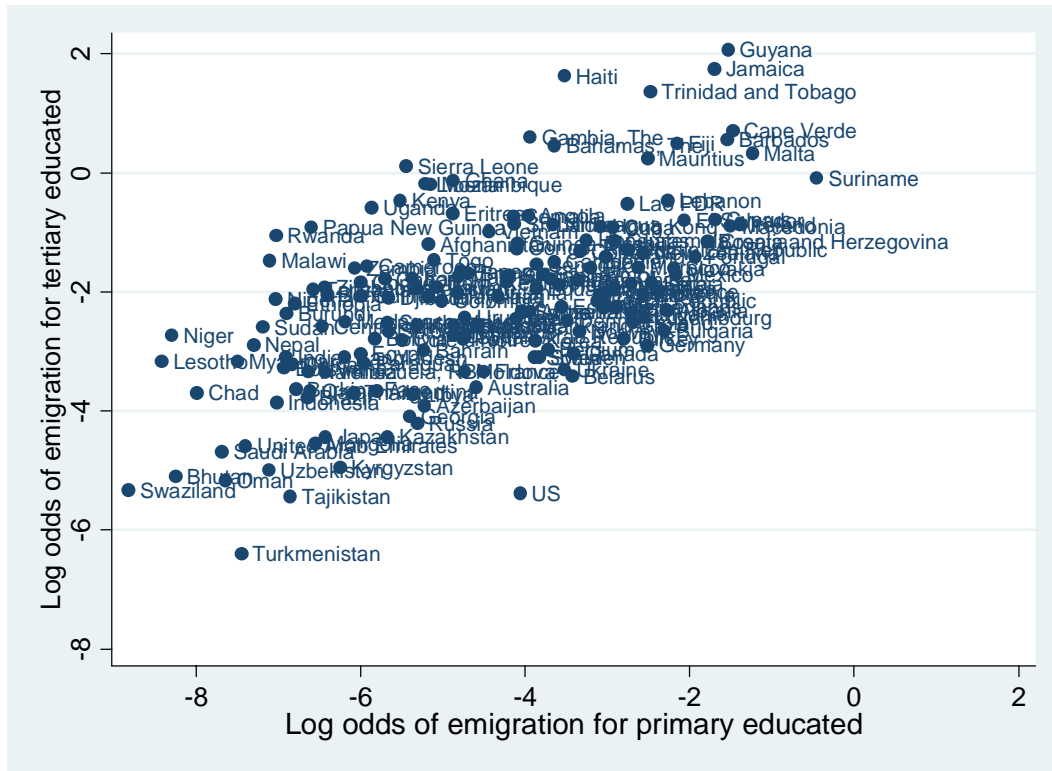


Table 1: Share of OECD immigrants by destination region and education, 2000

Destination Region	Education Group			
	All	Primary	Secondary	Tertiary
North America	0.514	0.352	0.540	0.655
Europe	0.384	0.560	0.349	0.236
Australia & Oceania	0.102	0.088	0.111	0.109
All OECD		0.355	0.292	0.353

Notes: This table shows the share of OECD immigrants by destination region and education group in 2000. North America includes Canada, Mexico and the United States; Australia and Oceania includes Australia, Japan, New Zealand, and South Korea; and Europe includes the other 24 OECD members (as of 2000).

Table 2: Share of emigrants to OECD by source country and destination region, 2000

Source country	Destination region			
	All OECD	N. America	Europe	Aus. & Oceania
Mexico	0.113	0.219	0.001	0.000
UK	0.053	0.041	0.027	0.206
Italy	0.042	0.027	0.062	0.038
Germany	0.038	0.028	0.049	0.045
Turkey	0.035	0.003	0.085	0.005
India	0.030	0.038	0.023	0.018
China	0.030	0.039	0.009	0.066
Philippines	0.030	0.046	0.007	0.030
Vietnam	0.022	0.032	0.008	0.026
Portugal	0.022	0.011	0.040	0.002
Korea	0.021	0.025	0.002	0.075
Poland	0.020	0.019	0.024	0.010
Morocco	0.019	0.002	0.048	0.000
Cuba	0.015	0.028	0.002	0.000
Canada	0.015	0.025	0.004	0.006

Table 3
Wage Differences, Pre- and Post-Tax, by Destination Country, in US\$1,000's

<i>A. Destinations included in the analysis</i>						
Destination country	Pre-tax			Post-tax		
	20th percentile (1)	80th percentile (2)	Difference (3)	20th percentile (4)	80th percentile (5)	Difference (6)
Australia	17.31	34.96	17.66	14.04	23.73	9.69
Austria	16.62	30.89	14.27	10.15	16.11	5.96
Canada	16.47	39.78	23.3	11.93	25.62	13.69
Denmark	27.68	54.49	26.81	16.26	26.06	9.8
France	13.62	30.36	16.74	7.86	14.5	6.64
Germany	24.84	48.08	23.24	13.29	21.32	8.03
Netherlands	27.99	47.37	19.38	16.88	26.44	9.56
Norway	23.07	49.99	26.92	15.16	27.84	12.68
Spain	12.14	26.05	13.91	8.05	15.37	7.33
Sweden	18.81	37.75	18.93	9.75	16.92	7.17
United Kingdom	22.44	48.6	26.16	16.5	31.97	15.47
United States	24.3	64.67	40.37	17.22	40.98	23.76
Mean	20.44	42.75	22.31	13.09	23.9	10.81

<i>B. Destinations excluded from the analysis</i>						
Destination country	Pre-tax			Post-tax		
	20th percentile (1)	80th percentile (2)	Difference (3)	20th percentile (4)	80th percentile (5)	Difference (6)
Belgium	18.55	33.45	14.9	9.31	12.8	3.49
Ireland	16.23	31.36	15.13	12.23	17.49	5.26
Italy	12.82	20.92	8.09	6.99	10.07	3.08
Mean	15.87	28.58	12.71	9.51	13.45	3.94

Note: Other destination countries were excluded since they have no micro data available from LIS. These include Finland, Greece, New Zealand, and Portugal.

Table 4
Results from Sorting Regressions

Dependent variable: Log skill ratio (tertiary/primary)				
Variable	(1)	(2)	(3)	(4)
Wage difference, pre-tax	0.070 (0.020)		0.039 (0.014)	
Wage difference, post-tax		0.131 (0.016)		0.080 (0.022)
English (destination country)			0.623 (0.294)	0.316 (0.343)
Common official language			0.404 (0.103)	0.405 (0.104)
Log distance			-0.010 (0.099)	0.015 (0.099)
Contiguous			-0.797 (0.188)	-0.743 (0.195)
Longitude difference			0.005 (0.002)	0.005 (0.002)
Colonial relationship, long term			-0.721 (0.189)	-0.753 (0.194)
Colonial relationship, short term			-0.347 (0.197)	-0.384 (0.188)
Visa waiver			0.208 (0.173)	0.225 (0.177)
Schengen signatory			0.910 (0.196)	0.933 (0.197)
Share asylees			-2.007 (0.736)	-2.028 (0.740)
R-sq	0.342	0.443	0.586	0.595

Notes: Sample size is 1993. Standard errors in parentheses are clustered by destination country. In addition to the variables shown, all regressions include a set of source-country dummies.

Table 5
Results from Sorting Regressions Based on Alternative Measures of the Wage Difference

Dependent variable: Log skill ratio (tertiary/primary)				
Variable	(1)	(2)	(3)	(4)
Wage difference	0.080 (0.022)	0.076 (0.029)	0.021 (0.006)	
Base wage				0.055 (0.048)
Skill markup				0.095 (0.030)
R-square	0.595	0.579	0.584	0.597
Adjusted for PPP in destination	No	Yes	No	No
Adjusted for PPP in source	No	No	Yes	No

Notes: Sample size is 1993, except for column (3), where sample size is 1811. Standard errors in parentheses are clustered by destination country. In addition to the variables shown, all regressions include a set of source-country dummies and all the variables shown in column (4) of Table 4.

Table 6
Results from Sorting Regressions Based on Alternative Specifications

Dependent variable: Log skill ratio (tertiary/primary)							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wage difference	0.080 (0.022)	0.079 (0.020)	0.053 (0.008)	0.093 (0.029)	0.067 (0.024)	0.059 (0.025)	0.085 (0.024)
Sample size	1993	1861	1993	1993	1963	1923	1993

Notes: Standard errors in parentheses are clustered by destination country. In addition to the variables shown, all regressions include a set of source-country dummies and all the variables shown in column (4) of Table 4.

Column (1): Baseline.

Column (2): Drop Germany as a destination, which defines immigration on basis of citizenship rather than birthplace.

Column (3): Include dummies indicating whether destination country data includes primary-only educational category.

Column (4): Numerator of skill ratio equals sum of secondary- and tertiary-educated migrants.

Column (5): Exclude source-destination cells where less than 3 percent of emigrants have primary education.

Column (6): Exclude source-destination cells where less than 5 percent of emigrants have primary education.

Column (7): Instrumental variables estimate. Instrument employs tax rates for families with children to compute post-tax wage difference.

Table 7
Results from Sorting Regressions That Include Additional Variables

Dependent variable: Log skill ratio (tertiary/primary)					
Variable	(1)	(2)	(3)	(4)	(5)
Wage difference	0.080 (0.022)	0.047 (0.021)	0.080 (0.023)	0.095 (0.026)	0.067 (0.024)
Relative university quality		-0.007 (0.002)			
Military bases			0.075 (0.181)		
Latitude difference				0.004 (0.004)	
Common minor language					-0.099 (0.145)
R-square	0.595	0.609	0.595	0.598	0.57

Notes: Sample size is 1993. Standard errors in parentheses are clustered by destination country. In addition to the variables shown, all regressions include a set of source-country dummies and all the variables shown in column (4) of Table 4.

Table 8
Mean Skill Levels Among Immigrants, by Destination Country

Destination country	Mean log skill share ratio	Mean share tertiary educated	Mean share primary educated	Immigrant skill gap
United States	1.93	0.57	0.11	0.00
Canada	1.27	0.67	0.22	0.66
Australia	1.20	0.55	0.20	0.74
Norway	0.80	0.33	0.17	1.13
Switzerland	0.56	0.28	0.16	1.38
United Kingdom	0.39	0.40	0.28	1.54
Sweden	0.21	0.36	0.29	1.72
Spain	-0.20	0.24	0.28	2.13
France	-0.32	0.37	0.48	2.25
Germany	-0.37	0.36	0.51	2.30
Denmark	-0.56	0.26	0.44	2.50
Netherlands	-0.58	0.26	0.46	2.51
Austria	-0.60	0.24	0.41	2.53

Note: Sample size is 192.

Table 9
Share of Immigrant Skill Gap with US Explained by Variables in Sorting Regression

Destination country	Wage diff.	English (dest.)	Common off. lang.	Log distance	Contig.	Long. diff.	Colony, long	Colony, short	Visa waiver	Schengen	Share asylees	Total	Residual difference
Australia	1.53	0.00	0.00	-0.01	-0.01	-0.15	0.00	0.00	0.00	0.00	-0.04	1.32	-0.32
Austria	0.56	0.12	0.04	0.00	0.01	0.09	0.00	0.00	-0.02	-0.03	0.22	1.01	-0.01
Canada	1.23	0.00	-0.08	0.00	-0.01	-0.01	-0.01	0.00	-0.03	0.00	-0.08	1.00	0.00
Denmark	0.45	0.13	0.05	0.00	0.00	0.09	0.00	0.00	-0.02	-0.03	0.20	0.86	0.14
France	0.61	0.14	0.02	0.00	0.01	0.09	0.05	0.00	-0.02	-0.03	0.11	0.99	0.01
Germany	0.55	0.14	0.05	0.00	0.02	0.10	0.00	0.00	-0.02	-0.04	0.03	0.82	0.18
Netherlands	0.45	0.13	0.05	0.00	0.00	0.08	0.00	0.00	-0.01	-0.03	0.31	0.97	0.03
Norway	0.79	0.28	0.11	0.01	0.00	0.19	-0.01	0.00	-0.04	-0.07	0.17	1.42	-0.42
Spain	0.62	0.15	0.03	0.00	0.00	0.10	0.04	0.00	-0.02	-0.04	-0.03	0.85	0.15
Sweden	0.77	0.18	0.07	0.00	0.00	0.13	0.00	0.00	-0.02	-0.04	0.20	1.29	-0.29
United Kingdom	0.43	0.00	0.00	0.00	0.00	0.12	0.16	0.00	-0.03	0.00	0.13	0.81	0.19
Mean	0.73	0.12	0.03	0.00	0.00	0.07	0.02	0.00	-0.02	-0.03	0.11	1.03	-0.03

Note: Based on model reported in column (4) of Table 4.