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ABSTRACT

Success of immigrants in the US, measured by earnings or education, varies dramatically by country of origin. Surprisingly, immigrants from Algeria have higher educational attainment than those from Israel or Japan. Another fact: The US admits few migrants from Algeria. Immigration slots are rationed and as a consequence, average immigrant attainment is inversely related to the number from a source country and positively related to its population and education level. The formal model's three variables explain 73% of the variation in educational attainment of immigrant groups in the US. The theory and predictions are bolstered by Swedish and Canadian data.

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Algeria, Israel, and Japan, along with over one hundred other countries, are sources of migrants to the United States. Try the following thought experiment: Rank those three countries' immigrants, highest to lowest, by educational attainment. The ranking is Algeria at the top followed by Israel and Japan. Surprised? Consider an additional fact: Algerians make up .0005 of immigrants, Israelis comprise .003 of US immigrants whereas about 1% of immigrants are from Japan. The largest origin country of US immigrants is Mexico, accounting for 27% of the immigrant population. Mexican immigrants rank 134th out of 136 in educational attainment, as compared with Algerian immigrants who rank 25th. Yet average education attainment in Mexico is higher than that in Algeria. The group with the highest educational attainment is that from the former Soviet Union, the most under-represented group among all immigrants in the US.

The attainment of immigrants in the US varies greatly by country of origin. Average educational attainment by country of origin ranges from a low of 9 years of schooling to a high of 16 years. Similarly, average annual earnings by country of origin ranges from about $16,000 to $64,000. Not surprisingly, the correlation between these two measures of attainment is .7. Additionally, two of the largest sources of US immigrants are at both extremes, with Mexico's migrants to the US having a mean educational attainment of 9 years, whereas India's migrants to the US have a mean of 16 years. Contrast that with the fact that the average educational level in Mexico is almost twice that of the average educational attainment in India. What explains these immigrant attainment differences across origin countries and the counterintuitive patterns?

Because the US admits as immigrants only a small fraction of most origin countries' populations, almost every country has a large enough group of highly educated people from which the US could draw its immigrants. Many of these individuals might be willing to move to the US if admitted. If so, then the average educational attainment of immigrants from any origin country depends in large part on whom the US is willing to admit. The more selective is immigration policy, the higher is the educational attainment of the group.

Important is that inferences about the quality of various countries as sources of immigrants are likely to be incorrect if they are based on the attainment of immigrants in the US from the particular country. The simple correlation between an immigrant's attained level of education and the average level of education in his or her origin country does not differ significantly from zero.[1] Mexico is not an inferior source country despite immigrants from Mexico ranking near the bottom in educational attainment. That is a result of the policy filter and selection criterion, not the inherent quality of Mexico's average educational attainment. A desirable destination country like the US could likely select high attainment immigrants from almost any country if that were the goal. In general, it is not. Other considerations such as refugee status as emphasized by Sweden or family reunification as emphasized in the US influence the admission choice and consequent attainment of immigrants.

Most models of immigration treat migrants as if they are mobile labor, moving from one

[1]The r-squared in a regression of immigrant's attained education on home country education using the American Communities Survey, as described below, is .02.

sector to another freely, without any constraints on the migrant imposed by policy.[2] These models have served analysts well in considering who chooses to come to the US, but they are less well-suited both theoretically and empirically in describing attainment of the immigrant population when excess supply and rationing of immigration slots is the rule.

Instead, supply plays a different and arguably more realistic role. Policy, explicit or implicit, determines the number of immigrants that are accepted from each source country. In the US, strong emphasis on family reunification means that there are many immigration slots for some countries and few for others. But given the number of slots, it is still necessary to determine which individuals come from each country. It is argued that selection is from the top and supply considerations may play a heavy role here.

There are, therefore, two types of selection at work. The selection emphasized in past literature is "personal selection," where an individual decides whether or not to migrate based on economic and other considerations. Generally ignored by the earlier literature is what might be called "process selection," where the destination country creates an admission system that results in a particular kind of selection through an explicit or implicit rule. Process selection is more important in countries that have excess demand for immigration slots. The system in the United States, which favors family reunification, is not neutral across countries and results in process selection. Because some origin countries are better represented among the current stock of immigrants, a seemingly neutral rule results in a non-neutral allocation of immigration slots. This occurs because the likelihood of having a relative already residing in the US varies by origin country.

Rationing of immigration slots is clearly important in the United States. For example, between 2009 and 2014, approximately 1 million individuals per year were granted permanent resident status. In each of those years, there was a large number of applicants who were in the queue for resident status, equaling about four times as many as the number granted permanent residency.[3] There is excess supply of immigrants, even by measures of those who apply. There are surely many more who would apply if they thought they would be admitted, but decline to do so because the likelihood that their application will succeed is too low. Each year, H-1B visas, awarded to individuals who are sponsored to work at US firms, run out well before the year ends.

Rationing also has a dramatic effect on performance of immigrants. To incorporate the importance of rationing and process selection, an extreme approach is adopted, albeit a caricature of the true situation. A desirable destination country is assumed to choose the number of immigrants that it will admit from each of the world's source countries. Selection is assumed to be from the top of that country's attainment distribution, either because the destination country uses that criterion of admission given the number admitted, or because those with higher levels of attainment are more likely to migrate. The latter could result from standard supply considerations, like the returns to migration being positively correlated with skill, or simply

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[2]Models, such as the one by Roy (1951) are frequently used to describe the flow of migrants to the US. See, for example, the seminal work by Borjas (1987).

[3]U.S. Department of State, Bureau of Consular Affairs, "Annual Immigrant Visa Waiting List Report as of November 1, 2015," 2015, and Department of Homeland Security, "Yearbook of Immigration Statistics 2014," 2016.

because those with higher attainment levels are better able to learn about and secure a scarce slot.[4] As a consequence, the shape of the education distribution in the origin country, the country's population, and importantly, the target immigrant number from that country determine the composition and attainment of immigrants in the US.

At some level, it is obvious that policy is a key determinant of immigration patterns. The large shift of migrants to the US from source countries in Europe to those in Latin America occurred after policy changed in 1965 favoring family reunification. There was no abrupt corresponding change in supply conditions. Natives of the West Indies and Surinam a make up 3% of the population of the Netherlands as a consequence of Dutch policy toward their former colonies. They account for only a tiny fraction of the US population despite those countries being geographically closer to the US than to Europe. The major presence of Algerians in France and minor presence in the US is a consequence of France allowing people from its former colonies to settle in the country. Of course, common language affects the desire to migrate to certain countries, but this factor does not explain time series changes nor the fact that the majority of immigrants in the US are not native English speakers. Supply considerations, by themselves, cannot rationalize the very different distributions of immigrants by country or origin across different destination countries, as will be shown by a comparison of Canada, Sweden, and the United States. Nor can supply considerations alone predict performance of the various immigrant groups in the destination countries. To deal with either of these issues, it is necessary to acknowledge the role that policy and rationing plays in the pattern of migration.

Although the point of this analysis is not unique to the United States, the focus is the US because the assumption that the process selection is paramount applies in the US better than in most of the world's countries. The excess supply of potential migrants to the US means that the rationing rule is a key factor in determining the nature of immigrants in the US. However, it will also be shown that data from Sweden, another desirable destination country, support the hypothesis. Furthermore, a comparison of sources of immigrants in the US and Canada, geographically similar countries with almost identical economies, make clear that supply cannot be the only factor in explaining immigration patterns and attainment.

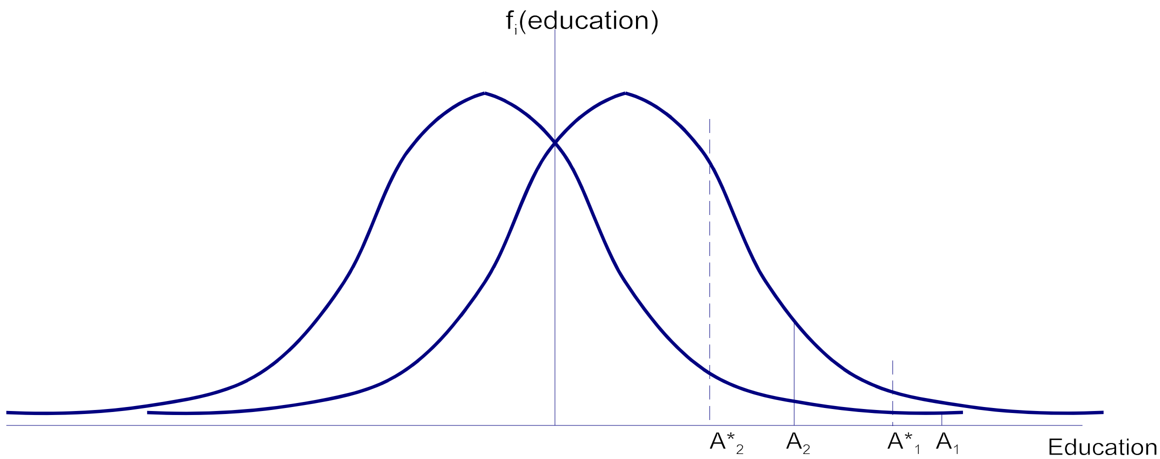
The model, which implies that three and only three variables should determine

[4] Borjas and Friedberg (2009) argue that selection rules explain the rise in wages of immigrants that occurred between 1990 and 2000. Additionally, Kerr and Lincoln (2010) examine the effect of the rise in H-1B visas on innovation and document its importance. Kerr, Kerr, and Lincoln (2015) use the LEHD data and find that skilled immigrant labor is an important determinant of the overall increase in the skilled workforce of American firms. H-1Bs are important because the H-1B program is always over-subscribed and the number of H-1Bs permitted is a policy choice that results in selection from the top, made by the US government.

Two Hunt papers, Hunt (2011) and Hunt (2015), examine the performance of highly skilled immigrants in the US. Another measure of ability to perform in the US relates to English fluency, which was explored in Lazear (1999). Lewis (2013) picks up on that theme and discusses the ability of immigrants to substitute for native-born US labor and how that relates to language skills. Similarly, Peri, Shih and Sparber (2015) estimate the effect of STEM immigration on productivity and find it is substantial, using city differences. None of these papers speaks to the empirical validity of the assumption that selection is from the top of an origin country's distribution, but the fact that many of the origin countries have low educational levels implies that the high skilled ones are selected from the top.

educational attainment does well. In the US, 73% of the variation in immigrant educational attainment is explained by the variables of interest in the model, namely the number of immigrants in the US, the population of the origin country, and the mean level of educational

Figure 1



attainment in the origin country.

Figure 1 illustrates the main argument. Consider two countries, 1 and 2, with equal population sizes and with educational distributions as shown. Country 2's distribution is a rightward displacement of country 1's distribution.

Suppose that the US were to decide that 3% of its immigrants will come from country 1, but that 30% will come from country 2 and suppose further that all who are offered US residency accept. If the US also allows only the most educated immigrants in first from each country, or alternatively, if the most educated in each country are most attracted to the US or most able to navigate their way through the immigration process, then the upper tail of each distribution will end up migrating to the US. In this case, because the US targets 3% from country 1 and 30% from country 2, the minimum cutoff level of education in each country is A_1* and A_2*, respectively. Note that the educational cutoff level for country 1, the lower education country, is considerably above that for country 2, the higher education country, because so many more are being admitted from country 2. Given the cutoffs and the underlying distributions, the average level of education among immigrants from country 1 and country 2 are A_1 and A_2. The educational attainment of immigrants from 1 exceeds that from 2, i.e., $A_1 > A_2$, even though country 1's education level at home is below that of country 2 at home.

Of course, this is not a necessary outcome. It depends on the amount by which country 2's education level dominates country 1 and in particular on the number of immigrants that the US admits from each of the two countries. But figure 1 illustrates that other things equal, the smaller the proportion of immigrants in the US who come from a country, the higher is the expected level of education of immigrants in the US who are supplied by that country.

Model

The general model captures the intuition of the figure and discussion. Suppose that the US chooses a selection rule such that I_i of the immigrants have origins in country i. The selection rule that determines I_i is taken to be exogenous, determined by policy, politics, or considerations outside the model.

Assume that anyone outside the US offered immigrant status in the US accepts it. Assume additionally that rationing is such that the top of the educational distribution (or any other dimension of immigrant ability) is admitted first. This can either be a result of explicit US policy or a consequence of the supply side, where the people most likely to come to the US from any other country are at the top of the ability distribution, the latter resulting either because they are best able to navigate the immigrate hurdles or because they have the highest return from migrating. This policy-determined selection of immigrants fits those who come in legally with official documentation. Those who enter the country without documentation are more likely to fit a strict supply-determined mechanism because the rationing rule chosen by the US does not bind.[5]

Let N_i be the population of country i and let $f_i(A)$ be the density of education or some other measure of ability or attainment, A, in country i.

It is not necessary to assume that anyone offered residency in the US accepts, although that is the most straightforward way to think about it. Another interpretation of $f_i(A)$ is that it is the transformed distribution that takes into account not only attainment, but also the proportion of those in country i with attainment level A who will migrate to the US if permitted to do so. The necessary condition in this case is simply that immigrants from countries that are admitted in higher quantities are a lower attainment group than those from countries admitted in lower quantities. Limiting the quantities of entrants has the effect of raising the average ability of those selected.

Given the policy determined I_i, A_i^* is the cutoff ability level of immigrants from country i determined such that

$$N_i \int_{A_i*}^{\infty} f_i(A)dA = I_i$$

or

$$N_i[1 - F_i(A_i*)] - I_i = 0 \tag{1}$$

The expected level of education among those from country i in the US is simply the conditional expectation or

[5]It is possible that the policy on internal enforcement and border control may have an effect even on those who do not apply through legal channels.

(2) $$\overline{A}_i = \frac{1}{1 - F_i(A_i^*)} \int_{A_i^*}^{\infty} A f_i(A) dA$$

The goal is to predict the effect of the key variables on the average educational level or other measures of attainment of a country's migrants to the US. Those variables are the number of immigrant slots allocated to country i, I_i, the population of country i, N_i, and the level of education in country i, μ_i, where μ_i is defined as the average level of education in origin country i.

To obtain the theoretical predictions, differentiate (2) with respect to I_i, N_i, and μ_i. In general, from (2), for any variable x,

$$\frac{\partial \overline{A}_i}{\partial x} = \frac{f_i(A_i^*) \frac{\partial A_i^*}{\partial x}}{[1 - F_i(A_i^*)]^2} \int_{A_i^*}^{\infty} A f_i(A) dA + \frac{1}{1 - F_i(A_i^*)} \int_{A_i^*}^{\infty} A \frac{\partial f_i(A)}{\partial x} dA - \frac{A_i^* f_i(A_i^*)}{1 - F_i(A_i^*)} \frac{\partial A_i^*}{\partial x}$$

or

(3) $$\frac{\partial \overline{A}_i}{\partial x} = \frac{f_i(A_i^*) \frac{\partial A_i^*}{\partial x}}{[1 - F_i(A_i^*)]} \left[\frac{\int_{A_i^*}^{\infty} A f_i(A) dA}{1 - F_i(A_i^*)} - A_i^* \right] + \frac{1}{1 - F_i(A_i^*)} \int_{A_i^*}^{\infty} A \frac{\partial f_i(A)}{\partial x} dA$$

The derivation in (3) allows the basic theoretical predictions to be stated. Most of the implications come directly from the properties of conditional expectations as interpreted in the current context. The theory is stated in the form of propositions, the proofs of which are contained in the appendix.

Proposition 1:

$$\frac{\partial \overline{A}_i}{\partial I_i} < 0 \ .$$

The larger is the number of immigrants admitted from country i, the lower is their expected level of attainment, $\overline{A}_i$.

Proposition 2:

$$\frac{\partial \overline{A}_i}{\partial N_i} > 0 \ .$$

For any given number of immigrants, I_i, the larger is the population in country i, the higher is the expected level of attainment of immigrants $\overline{A}_i$ from that country.

Finally, let $F_i(A) = F(A-\mu_i)$ so that every country's ability distribution is of the same form, but merely displaced by country-specific parameter μ_i. Countries with higher μ_i values have higher ability distributions. Assume further that f '(A) is negative for all $A \geq A_i^*$. This is likely to hold empirically under the assumption that the most able are taken first because there is no country that provides so many immigrants that the cutoff ability, A_i^*, would not be in the upper tail of the ability distribution, which is expected to be negatively sloped. Then,

Proposition 3:

$$\frac{\partial \overline{A}_i}{\partial \mu_i} > 0$$

Immigrants from countries with higher levels of attainment have higher attainment in the destination country.

It is also possible to express the concepts in propositions 1-3 in terms of the "representation ratio" defined as

$$R_i \equiv \frac{I_i / \sum I_i}{N_i / \sum N_i} \qquad .$$

R_i should be interpreted as the over-representation of country i among immigrants, given the country's relative population importance. If R_i equals 1, the proportion of immigrants in the US from country i reflects its weight in the overall population of the world. If R_i exceeds 1, that country is over-represented among US immigrants. If R_i is less than 1, then country i is under-represented among immigrants in the US. Note further that R_i is simply the ratio of immigrants from i to the population from i, I_i/N_i, times a scalar that measures the proportion of total immigrants taken by the destination to the world population, $\sum I_i / \sum N_i$. This will be employed later in testing functional from and other implications.

The representation ratio is a useful concept for understanding some patterns that emerge. For example, India is highly under-represented among immigrants by a factor of almost four, despite the fact that Indians are the third largest group of immigrants (behind Mexicans and Filipinos). In contrast, Jamaicans are highly over-represented, making up over forty times the number of immigrants as would be expected given Jamaica's population even though there are only one-third as many immigrants from Jamaica as there are from India.

It is then possible to state a corollary to propositions 1 and 2 in terms of the representation ratio:

Corollary 1: Given a fixed number of immigrants,

$$\frac{\partial \overline{A}_i}{\partial R_i} < 0$$

At any point in time, the number of immigrants is given. Therefore countries with higher representation ratios have lower expected levels of attainment $\overline{A}_i$.

Additional theoretical predictions can be derived. The model provides implications not only for immigrants and their relative standing in the recipient country, in this case the US, but also for their situation vis à vis the general population of the origin countries. For these purposes, define A_i as referring to and only to levels of attained education. Let

$$\Delta \equiv E_i(A \mid A>A_i^*) - E_i(A) \equiv \overline{A}_i - \mu_i$$

where E_i is the expected level of education within country i, given the distribution of education $f_i(A)$ in country i. Then Δ is interpreted as the difference between the attained education of immigrants in the US from country i and the average level of education of the overall population in country i.

Recall that $\overline{A}_i \equiv E_i(A \mid A>A_i^*)$ so

$$\Delta \equiv \frac{1}{1-F_i(A_i^*)}\int_{A_i^*}^{\infty} Af_i(A)dA - \int_{-\infty}^{\infty} Af_i(A)dA$$

The empirically verifiable implications are stated as corollaries here and proved in the appendix.

Corollary 2: $\partial\Delta/\partial I_i < 0$.

The difference between the mean education of immigrants from origin country i and the mean education of the population of that country falls in I_i.

Corollary 3: $\partial\Delta/\partial N_i > 0$.

The difference between the mean education of immigrants from origin country i and the mean education of the population of that country rises in N_i.

Corollary 4: $\partial\Delta/\partial\mu_i = 0$.

Under the assumptions above, a shift in the mean of the origin country's education distribution is neutral, having no effect on the difference between the mean education of immigrants from that country and the mean education in the origin country's overall population.

Equivalently, if $I_i = I_j$ and $N_i = N_j$, then the difference between the mean level of education among immigrants from country i and country j equals the difference between the mean level of education in the origin countries' overall population.

Discussion

The logic behind the propositions and corollaries fits the example in the introduction and the data on immigrant background and attainment, both education and earnings, in the US.

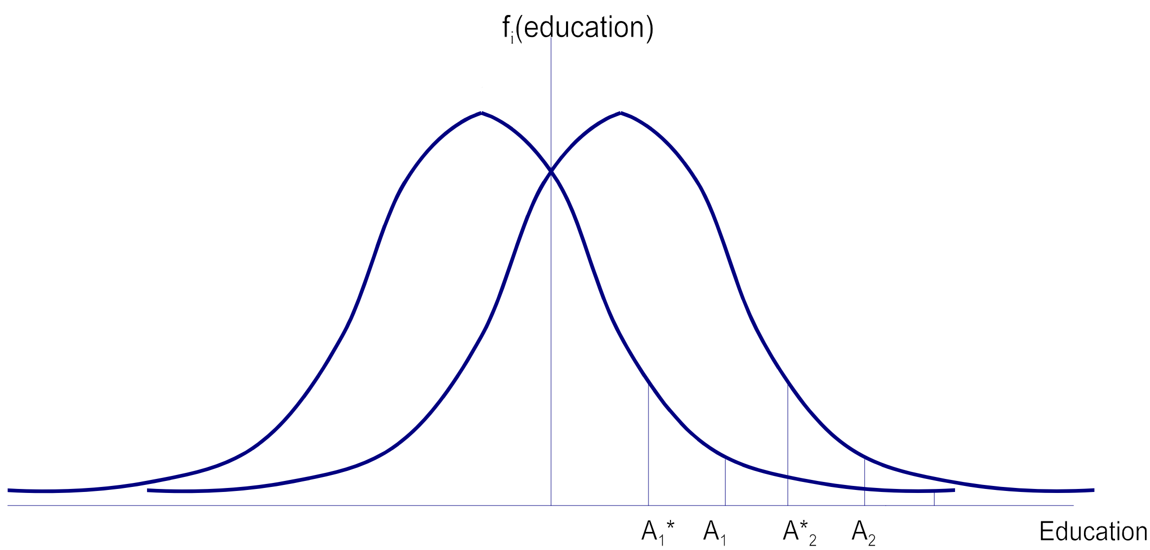
Proposition 1 predicts the basic point made at the outset. When a country is permitted to send only a small number of immigrants and when selection is from the top down, those who enter the US will be highly talented. The group with the highest level of educational attainment came from the USSR. Note that this is "USSR," not Russia, which means that they entered before the breakup of the Soviet Union. Among the pool of immigrants in the sample, there were only 400 from the former Soviet Union as compared with over 395,000 from Mexico, the largest source of US immigrants. The former Soviets were a rare group, needing to obtain both exit permission from the USSR as well as entry permission from US. A large proportion were highly-educated political dissidents, many of whom were elite academics. The same is true perhaps to a lesser extent of other countries, like Algeria. The average level of education in Algeria is well below the mean for origin countries, but those who succeeded in moving to the US were not typical Algerians. Instead, they were more educated than their compatriots, so much so that as a origin country, Algeria is in the top 20% of immigrant groups to the US in educational attainment. Algerians make up less than .0005 of US immigrants - a tiny fraction - and those who have been admitted to the US have been selected for reasons that correlate well with education. The same educational attainment would not likely be found of Algerian migrants to France, where they make up a much larger fraction of the immigrant population.

Proposition 2 is slightly more subtle, but almost equally intuitive. Consider selecting the most highly educated 1 million people from a tiny country like Laos with 7 million people versus 1 million from India with 1.3 billion. If the distribution of underlying ability were the same in both countries, A* for India would be higher than A* for Laos because 1 million people comprise a much smaller fraction of the top tail of the distribution when there are 1.3 billion than when there are 7 million. In fact, that is what is seen in the data. A substantial fraction of US immigrants come from India, comprising almost 5% of the sample of immigrants. But because India is so large, India is very much under-represented (by a factor of almost four), given its importance in world population. As such, those who come from India are from the top part of India's educational distribution. India itself is not a country with a high average level of education. Only 14 countries in the world have lower average levels of education than India has. However, because US immigration policy does not select randomly from origin countries nor from individuals within each country, Indians in the US rank second among immigrants in educational attainment.

Proposition 3 makes the more intuitive point that the more highly educated are people in the home country, the more educated are those who immigrate from them. Consider two countries with exactly the same populations and that make up exactly the same proportion of US immigrant pool. If the ability distribution from country 2 lies to the right of that from country 1, then selecting the same fraction of the upper tail from each results in a higher average level of education among those selected. This is shown in Figure 2. Two countries, 1 and 2, have similarly shaped distributions of talent, but country 2's distribution is a rightward shift of country

1's distribution. Consequently, A_2* exceeds A_1* by the difference in their means, i.e., $\partial \overline{A_i} / \partial \mu_i$ should equal 1. Furthermore, as is the subject of corollary 4, A_2, defined as the expectation of ability among immigrants from 2, exceeds A_1, defined as the expectation of ability among immigrants from 1, by the difference in their means. This is equivalent to the statement that A_2 exceeds the mean of distribution 2 by the same amount that A_1 exceeds the mean of distribution 1.

Figure 2



Corollary 1 simply states propositions 1 and 2 in another intuitive form. A country can be over- or under-represented among immigrants. When a country is over-represented, the cutoff level of ability from that population must be lower than it would be were that same country under-represented among immigrants.

Corollaries 2, 3, and 4 follow directly from the model, but empirically, they are different tests of the model's logic. The dependent variable in the corollaries is Δ_i, which is not the same as $\overline{A}_i$. The average attainment among immigrants from country i, $\overline{A}_i$ could be high relative to that from country j, $\overline{A}_j$, but that does not imply mechanically that $\overline{A_i}$ is high relative to the average level of education in country i. For example, immigrants from the United Kingdom have average schooling attainment of 15 years, above the immigrant mean. But the average level of education in the UK is well above the mean education for other countries in the world, so the value of Δ for the UK is low. Conversely, immigrants in the US from Yemen have only 9 years of schooling, but the average level of education in Yemen is only 2.5 years, resulting in a high value of Δ. Obviously, as a statistical matter, Δ_i and $\overline{A_i}$ may be related because the former contains the latter, but they are not the same. Corollaries 2-4 provide additional predictions that can be tested and could be rejected, even were propositions 1-3 to hold empirically. Furthermore, note that the predicted relation of Δ to μ_i is zero, not negative as would result from pure statistical bias.

In the analysis below, attainment among immigrants is measured by three different variables, namely average education, hourly wages among working immigrants, and average earnings among all immigrants from a particular country.

Without exception, all predictions of propositions 1 through 3 and corollary 1 are borne out for all three measures. Corollaries 2-4 are found to hold with respect to educational attainment, but cannot be tested for the two income variables because the data do not contain information on income for the most of the 129 origin countries used in the analysis.

Specific Distributions of Ability and Implied Structural Estimates

Under more specific assumptions, the propositions and corollaries stated above can be parameterized. This approach has the advantage that it allows for interpretation of estimates, but more important, it provides additional checks on the credibility of the model and its assumptions.[6]

To begin, suppose that each origin country has a normal distribution of A with a country-specific mean μ_i and country-specific variance σ_i^2 . Recall that I_i is the exogenously determined policy variable. Let F_i^* denote the cumulative normal distribution with mean μ_i and variance σ_i^2. Further, let f_i^* be the normal density with mean μ_i and variance σ_i^2. Then, from (1), A_i^* can be determined as

(1') $N_i\,[1-F_i^*(A_i^*)] - I_i = 0$

and similarly

(2') $$\overline{A_i} = \frac{1}{1-F_i*(A_i*)}\int_{A_i*}^{\infty} Af_i*(A)dA$$

If all the μ_i and σ_i were known, the exact $\overline{A_i}$ for each country i would be determined, given μ_i . That is, once the country's ability distribution is known precisely and once A_i^* is given, it is straightforward to calculate the conditional expectation of those who are above A_i^*. Then a goodness-of-fit statistic can be computed by checking to see how well the actual $\overline{A_i}$ compare to those predicted based on the observed μ_i of the origin country and σ_i.

The data below provide an average attained level of education for the 129 countries

[6]I ask the reader to excuse my self-indulgence for pointing out that one of (if not the) first structural estimation approaches in labor and applied microeconomics appeared in my 1977 paper on a different topic. See Lazear (1977).

studied so that μ_i is observable. The only missing parameter is σ_i but this can be obtained for a subset of countries using and additional dataset (IPUMS, as described below).

Data

The primary data on attainment of immigrants in the US come from the American Community Survey from years 2011 through 2015. This is a series of five consecutive cross-sectional data sets. By combining years, a larger sample is created so that more precision can be obtained. It is straightforward to adjust standard errors for population weights and to correct wage data for inflation to turn nominal wages and earnings into real values. Given the individual data, the means of attainment variables, namely, education, wages, and annual earnings can be computed by country of origin.

The variables of interest are those that measure attainment of the immigrants once in the US. They include educational attainment, wages, and income. The independent variables are either internally constructed, as is the case for I_i, or drawn from other data sets. UN reports provide information on average education within the origin country and population statistics are taken from World Bank data. For convenience of reading the tables, I_i is defined as the actual number of immigrants from country i, measured in millions as estimated by scaling up the ACS data to reflect sample size relative to overall population. Similarly, N_i is defined as the population of country i in 100 millions. Additionally, information on GDP per capita, share in agriculture, growth rates, proportion with tertiary education and distance of the origin country from the US is obtained. Appendix B contains the sources for each of the variables used. Additionally, data from Sweden described in a later section is used to corroborate findings and distinguish the hypothesis here from other explanations.

Results

The main results are presented in tables 1 through 3. Table 1 tests the propositions using the average educational attainment of immigrants from country i as the dependent variable. There are 129 countries with information necessary for the analysis. For each of those countries, observations on each individual in the ACS sample is used. The 129 observations consist of origin-country averages among those immigrants who are in the ACS sample. Note that the country-based immigrant weighted regressions reported in tables 1-3 are equivalent to using the raw individual-based ACS data, but the country versions are reported because the variation in I_i, N_i, and μ_i are at the country, not individual levels. Later, individual data are used to examine cohort and age-of-arrival effects.

Columns 1 through 4 of table 1 use different weighting schemes and subsamples. Column 1 is a full sample analysis where countries are weighted by the number of observations that are used to compute the mean of the dependent variable. This is equivalent to using the individual data (analyzed below in table 8) from which the country means are drawn. Column 2 presents the same analysis on the same sample, but weights every country equally. The results are similar, both in terms of sign and statistical significance. All the propositions are supported by these results. Specifically, the average educational attainment of immigrants from country i declines in $I_{i,}$ as predicted by proposition 1, increases in N_i, as predicted by proposition 2, and increases in μ_i as predicted by proposition 3. Furthermore, the three variable model explains 73% of the variation in immigrant educational attainment (column 1).

In accordance with proposition 1, a one standard deviation increase in a country's number of immigrants decreases the predicted level of educational attainment in the US by about .4 years on a mean level of education of 13.4 years. The predicted difference in education among immigrants from the highest immigrant provider, Mexico, and the lowest immigrant provider, Estonia is 4.3 years. The actual difference between immigrants from the two countries is not far off at 5.6 years in favor of those from Estonia.

Proposition 2 predicts that the larger the population of the origin country, the higher is the attained level of education among immigrants. A one standard deviation increase in the population of the origin country implies about .4 of a year increase in the education levels of the immigrants from that country. (Coincidentally, this is the same number as a one standard deviation change in I_i produces.) Compare a tiny country like Cape Verde with ½ million people to a large country like Nigeria with almost 200 million people. Both have similar average levels of education, but in accordance Proposition 2, the average level of education among immigrants in the US from Cape Verde is 9.8 years versus over 15 years for those from Nigeria.[7]

The more intuitive prediction of proposition 3, that the education of immigrants from country i is positively associated with education among natives in country i, is borne out by the positive and significant coefficients on μ_i in table 1. A one standard deviation increase in the mean level of education in the origin country implies about a one year increase in education among immigrants. This is not completely consistent with the theory, however. The coefficient should be 1, as mentioned above (see the proof in the appendix of proposition 3, which yields the result that $\partial \bar{A}_i / \partial\mu_i = 1$). The coefficient in table 1 on μ_i is always less than one. Some of this may be attributed to an errors-in-variables issue, where μ_i is mis-measured, but the coefficient is substantially below 1, seeming to deviate from the literal prediction of the model that assumes the distribution distribution across countries up to a shifter in the mean.

Finally, table 1, columns 7 and 8, speak to corollary 1, where the representation ratio is used in place of I_i and N_i . Corollary 1 is supported by the results, which yield negative and statistically significant coefficients. Recall that India is very much under-represented among US immigrants, despite being the third largest supplier of immigrants. Because India is the second most populous country in the world, it is under-represented by a factor of 4 among US immigrants. The implied difference between the education of immigrants from India and that from, say, El Salvador, which is highly over-represented is about 3.5 years based on this factor alone. The actual difference is about 6 years.

About 73% of the origin country variation in educational attainment is explained by these three variables alone (in column 1). Importantly, almost all of this is driven by the primary

[7]The actual difference is much greater than that predicted from the coefficients in table 1, but the direction and nature of the effect is as predicted. Also, there are about 6 times as many immigrants from Nigeria as there are from Cape Verde, but there are 400 times more people in Nigeria than in Cape Verde. Indeed, Cape Verde is over-represented among immigrants by a factor of 12, whereas Nigeria is under-represented by a factor of 5.

rationing variable, I_i . The r-squared in the weighted I_i regressions of A_i on I_i alone is .55, of A_i on N_i alone is .09, and of A_i on μ alone is .02.

Columns 3 - 6 repeat the analysis, but with different sub-samples. In columns, 3 and 4, the four largest origin countries of immigrants are omitted to ensure that the results are not driven by a few countries. In columns 5 and 6, the smallest countries are omitted. Qualitatively, the results are unchanged, although the magnitudes do change some, especially and not surprisingly for the coefficient on N_i, because the omission of very large population countries changes the scale of that factor.[8] Additionally, the conclusions are robust to weighting and sample choice.

Table 2 performs the same analysis, but defines attainment in terms of the hourly wage received among those working rather than educational attainment.[9] Columns 1 through 7 of table 2 mirror columns 1 through 7 of table 1, with all signs and statistical precision being similar across dependent variable definitions. A one standard deviation decrease in I_i implies about a \$1.39 increase in the wage on a mean wage of \$30.42 and a one standard deviation increase in the N_i implies a \$2.24 increase. Just as was the case for education, the larger the number of immigrants from an origin country, the lower is the average wage, and the larger is the population of the country, the higher is the average wage among those immigrants. Additionally, the higher is the level of education in the origin country, which serves as a proxy for the average wage in the origin country, the higher is the immigrant wage. Indeed, substituting GDP per capita for education as a proxy for wage in the origin country gives essentially the same results. Also, as was the case in table 1, all robustness checks on weightings and sub-samples confirm the initial results of the first column.

Table 3 is analogous to table 2, but the dependent variable is average earnings among all immigrants from country i. This takes into account wage conditional on working, as in table 2, but also is affected by hours of work and employment rates among the immigrant population. Again, results are qualitatively identical.

The effects estimated in table 3 can be quite large. For example, the predicted difference between average earnings of those from the Philippines, which supplies the second largest fraction of US immigrants and Mexico, which supplies the most, is \$13,297 in favor of Philippines. Although Filipinos are the second largest group of US immigrants, there are almost five times as many Mexican immigrants in the US as Filipino. That difference accounts for the much higher predicted income for Philippine immigrants. The actual difference between the two groups is about \$16,300 in favor of the Philippines. Note that both origin countries have average levels of education of around 9 years, so the origin countries are comparable at least in this respect.

Corollary 1 has already been discussed in the context of tables 1-3. Corollary 1 simply

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[8]A variable measuring population squared does not enter significantly in the weighted regression, but enters positively as predicted in the unweighted version.

[9]The dependent variable is in absolute dollars. The linear specification is appropriate for country means, but not for the individual-based data used below. Income distributions are approximately log normal at the individual level, but should be normal for means. The actual distribution of country means exhibits some positive skew.

condenses propositions 1 and 2 into the representation ratio, which is analyzed in columns 7 and 8 of the three tables. As discussed earlier, the data strongly support the contention of corollary 1, namely that the lower the representation ratio, the higher the achievement of a given country's immigrants in the US.

Corollaries 2-4 are testable in the same way that Propositions 1-3 were tested, with two exceptions. First, because there is no direct measure of average wage or earnings for all the countries in the dataset, the analysis is restricted to estimating only Δ defined in terms of education, namely the education of immigrants from country i minus the average level of education in country i.[10]

Second, there is a standard statistical problem introduced by regressing Δ on independent variables that include μ because μ is part of Δ. Recall that Δ is defined as $\overline{A}_i - \mu_i$, so any measurement errors in μ_i bias the coefficient on μ_i downward. The standard solution for this problem is to instrument the independent variable, in this case, using something that is correlated with μ_i but does not have the same measurement error associated with it. Fortunately, there is another measure of education at home that is correlated with average education (as is evidenced by the first stage), but is not the same variable. The proportion of the population with tertiary education from Barro and Lee (2010) is a measure of a country's education level that is different from μ_i but related to it. That variable is used as an instrument.[11]

Table 4 reports the results. Column 1 provides the estimates from the instrumental variables approach. As corollary 2 predicts, the sign on I_i is negative and as corollary 3 predicts, the sign on N_i is positive. The larger is the group of immigrants in the US, the smaller is the difference between the immigrants' educational attainment in the US and the average educational attainment of the population in the origin country. The larger is the population of the home country, the larger is the difference between the immigrants' educational attainment in the US and the average educational attainment of the population in the origin country. Finally, as predicted, the effect of μ is not significantly different from zero. Of course, the failure to find a significant effect of μ does not imply that corollary 4 is proved, but merely that it is not refuted and the standard error is large enough to prohibit ruling out a sizeable effect of μ_i. The r-squared from the first stage is .54 with an $F(1, 66) = 28.1$, which provides some additional evidence on the validity of the estimates.

Column 2 reports the OLS results. They are similar, with the exception of the coefficient on μ, which, not surprisingly, is negative. Entering the same variable on both sides of the equation results in bias, in this case negative.

Functional Form

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[10]It is important to use measures that are on the same scale, particularly with respect to proposition 4. The closest to wages or earnings in the US would be purchasing power parity GDP per capita, but this would not be a good proxy of comparable earnings at home if for no reason other than scaling.

[11]Under the assumption that $F_i(A_i) = F(A_i - \mu_i)$, it is only the mean of the distribution that matters, in which case the proportion with tertiary education is a valid instrument. However, a more general specification that allows the entire distribution to vary might have higher moments of the distribution included and the tertiary instrument would only be valid if those other moments were included.

Equations (1) and (2) imply homogeneity of degree zero in I_i and N_i. Specifically, changing both I_i and N_i proportionately should not alter attainment among immigrants because A_i*in (1) is not affected when both are multiplied by any factor λ. Multiplying I_i and N_i by λ in (1) gives

$$\lambda N_i[1-F_i(A_i*)]-\lambda I_i=0$$

which reduces to equation (1) so A_i* is independent of the scalar. Additionally, since $\overline{A}_i$ in (2) depends only on A_i* and on $f_i(A)$, neither of which changes with λ, $\overline{A}_i$ is not affected by λ. This is testable. It implies that attainment across immigrant origin countries should only depend on the ratio of I_i to N_i and on μ_i, which locates the origin country's attainment distribution, but not on the absolute levels of I_i and N_i directly. Table 5 tests this homogeneity implication and explores other functional form issues.

Columns 1 and 2 report the results when only the ratio of I_i to Ni and μ_i are included as independent variables. The mean education in the home country should be included even in the form that tests heterogeneity because the distribution is permitted to shift across countries. Recall that the representation ratio is merely I_i/N_i times a scalar relating the world population to the number of immigrants in the US. Thus, the homogeneity property is equivalent to saying that neither I_i nor N_i should affect the cutoff and therefore attainment, given the representation ratio.

In table 5, column 1 weights by number of immigrants from country i and column 2 is the unweighted version. In both forms, the ratio enters negatively, as predicted. Compare column 1 with column 3 and column 2 with column 4, the latter two allowing I_i and N_i to enter directly. The homogeneity property is clearly violated in both weighted and unweighted versions with I_i continuing to enter negatively and N_i entering positively.

There are a number of possible explanations. Recall that the assumption was that the distribution of A was identical across countries up to a shifter in the mean, μ_i. That assumption is violated. Specifically, large population countries have a higher conditional expectation than would be predicted, which suggests a thicker upper tail in larger countries. One possibility is economies of scale in educational production. For example, India has top technical universities. Smaller countries with equal per capita GDP cannot afford to support major educational institutions. If true, there would be disproportionately more highly educated individuals in large countries than in small countries, which would thicken the upper tail and result in a positive coefficient on N_i. This is in fact the case. The next section provides structural estimates and drops the assumption that $F_i(A) = F(A-\mu_i)$, i.e., that all source countries have the same distribution of education (at home) up to a mean shifter. There, country-specific education data from IPUMS[12] is used for a subset of countries. Those data reveal that India has one of the highest standard deviations and coefficient of variations of within-country education levels. Despite having a very low average level of education, there is a significant fraction of Indians who are highly educated, some of whom migrate to the US, many through the H1-B program. As mentioned at the outset, Indians are highly under-represented in the US, but those who are

[12]International Public Use Microdata Series (2018).

here tend to come from the top tail of the educational distribution.

China is a somewhat different case, having a higher mean education than India, but a much lower standard deviation and coefficient of variation. Still, because China is so large and because 10 percent of the Chinese population have completed the equivalent of high school, there are many Chinese with high levels of education who might be willing to move to the US.

The negative coefficient on I_i may be driven by different immigration policy selection rules for countries that account for many versus few immigrants. In the case of countries that account for only a small number of immigrants that are under-reprensented in the US (like the USSR or African countries that fit the Algerian example), skill rather than other factors may be a more important consideration. Family reunification is likely to play a greater role for those countries that have large numbers of immigrants in the US. As a consequence, I_i enters negatively, even holding constant the ratio of I_i to $N_{i,}$ because small countries fit the selection-from-the-top assumption more closely.

The final two columns report the results when logs rather than levels are used. Unsurprisingly, the results are not affected qualitatively.

Structural Estimates

The structural approach that assumes normality of the attainment distribution, outlined at the end of the model section, can be implemented. The details of the estimation are described in Appendix C. Briefly, for a subset of the countries used in the tables above, IPUMS data are available. They provide information on the actual level of education of individuals within the countries. The original dataset had over 700 million observations, but a random sample of 10,000 observations from each of 66 countries was selected so that in addition to the mean, the standard deviation and 90th percentile of educational attainment could be computed.

Before engaging in structural estimation, as a check, the reduced form regression in column 1 of table 1 is re-estimated using the subset of 66 countries. The coefficients change slightly, but are fundamentally the same as those on the sample of 129 countries. The r-squared for the table 1, column 1 regression rises slightly to .75 from .73 when the sample is restricted to the 66 countries for which IPUMS data are available instead of the original 129 countries. The addition of the standard deviation of the education in the source country enters positively, although just below standard significance levels (t=1.89). (The coefficient on the 90th percentile was close to zero.) The interpretation makes sense. Those source countries with the most variation in education for a given mean have a fatter upper tail, which results in a higher conditional expectation of educational attainment among immigrants.

The structural estimation is performed as follows. The IPUMS data provide the mean and standard deviation of education in the source country. Given those values, the actual upper tail of the educational distribution for each country can be calculated, getting a predicted A_i* based on the Ii/N_i ratio for each country-specific distribution of education. Once A_i* is obtained, a predicted average level of attained education among immigrants, namely those whose education exceeds A_i*, can be calculated for each of the i countries. Goodness-of-fit of the structural model can be calculated by regressing the actual $\overline{A}_i$ on the estimated one.

When this is done on the subset of 66 countries for which IPUMS data are available, the r-squared of actual on predicted is .62. Thus, the structural model does 83% as well in explaining the data as does the reduced form. (The ratio of r-squareds in structural and unconstrained reduced form is .62 / .75 = .83.)

Additional Considerations

Other Explanatory Factors

Table 6 allows other variables that are not explicitly modeled to affect the educational attainment of immigrants in the US. The inclusion of other factors raises the explanatory power by about 15 percentage points, from .73 to .88 in the weighted version of column 1. In particular, variables that measure growth and stage of development are included, as is the origin country's distance from the US (capital city to Washington, DC). The variables that measure stage of development include GDP per capita, the last five years' growth rate, and the share of GDP that is comprised of agricultural output. Those variables are highly correlated particularly with I_i and with μ_i and a regression of educational attainment on only the supply variables results in an r-squared that is almost the same as that for the three variables of the model. Consequently, regressions of educational attainment on rationing variables as well as the additional variables is most informative to see which drive the results.

The results in table 6 show that none of the additional variables remain significant through all specifications. The opposite is true of the variables predicted by the model. Those coefficients maintain sign and significance throughout all specifications. Although the magnitudes are somewhat different from those found in table 1, the basic story remains the same.

In the preferred specification of column 1, the coefficients on distance, the GDP growth rate, and agriculture's share of GDP are significant. The latter two suggest that the less developed and less rapidly growing is the economy, the greater is the incentive for high education individuals to seek residency in the US. This seems more consistent with a supply side explanation and recall that the supply side is expected to play an important role in making valid the assumption of selection from the top.

Distance of the origin country from the US is also significant in column 1 and might be associated with more traditional supply-side explanations. Immigrants who are further away must bear larger costs to come to the US and this would be a barrier that might cut most for lower skilled migrants. This explanation, while plausible, is questionable for a few reasons.

First, the result is driven entirely by the four largest origin countries: Mexico, Philippines, India and China. When those countries are excluded or when each of those four countries is allowed to have its own fixed effect, the importance of distance as an explanatory variable vanishes.

Second, India, China and the Philippines are all distant from the US. Immigrants from India have high levels of education, those from China are slightly below the median and those from the Philippines are slightly above. Similarly, Mexico and Canada each border the US. Canadian immigrants have over five years more education on average than those from Mexico. Additionally, Mexicans are three times more over-represented among US immigrants than Canadians, despite equal distance of travel, which suggests that distance cannot be the primary determinant of migration patterns.

Third, the correlation between the number of immigrants from an origin country and distance is small, equaling -.11 and not statistically significant. This is not surprising because unlike in the past, in the 21st century distance is not much of an impediment to movement. The cost of airplane ticket even from distant countries to the US is low. For example, a quick online search shows that a ticket from Delhi to New York can be purchased for $711. The difference in earnings between the US and origin countries, even for low skilled immigrants, is on the order of $11,000 per year.[13]

In one of the four specifications, column 1, share in agriculture and growth are significant. Their signs suggest that the highly educated flee countries that are stagnant and agricultural. This is consistent with a supply story. But again, the result is driven by the four large countries, primarily India. India does not fit the supply story alone. Although the US tends to get highly educated Indians, as supply would suggest, they are very much under-represented among US immigrants. If supply were the only factor, one would expect large numbers of educated Indians entering the US. The fact that Indians also make up a significant fraction of those applying for H-1B visas and that those visas run out long before demand is satisfied suggests that rationing must be a major part of the explanation.

The conclusion from the empirical analysis is that the model works well in predicting who ends up in the US. Although supply considerations may matter, particularly in determining who is successful in being admitted to the US, a structure that assumes that all who are admitted come and that the US admits from the top of the attainment distribution of each country after determining how many to admit from each county explains the data well. All predictions are borne out and the structural model provides a good fit with the data.

Explicit Policy Deviates from that Assumed

In a typical year, over 60% of those issued permanent resident status are family sponsored. Although this does not rule out that those individuals are from the top of the educational attainment distribution at home, it does not appear to be a criterion that is closely related to selecting the most able from each country.

Even though the model is admittedly stylized, it would be useful to find some evidence that lends some credence to its assumptions and especially the assumption that potential migrants are selected from the top of the origin country's attainment distribution.

There is at least some support for the view that immigrants are selected from the top of the distribution. Recall that Δ_i is defined as the difference between the average educational attainment among immigrants and the average attainment in origin country *i*. To the extent that immigration slots to the US are scarce and desirable, ability may come into play in finding ways to make it into the US. Some of this is explicit. A number of skills-based green cards are issued to highly educated foreign citizens who eventually become residents and citizens of the US. But given the number who enter through other legal channels, not to mention those who come in illegally, it is worth exploring the validity of the assumption that the highly able from any given country are selected into the United States. In 129 out of 129 cases, Δ_i is positive, meaning that the average educational attainment of immigrants from country i exceeds the average level of education in country i. The difference averages 4.8 years, with a low of ½ year and a high of 11 ½ years.

Although supportive of the assumption, the evidence is not conclusive because

[13]See Hanson, et. al., (2017) and my comment on that paper in the same volume.

educational attainment of those who are in the US might be higher than that of those who remain in the origin country if for no other reason than the US has higher average education than the world as a whole.[14] It is possible to rule this out by using the raw ACS data from which the country averages are computed. (These data form the basis for additional analyses below.) The raw ACS data allow an examination of individuals who came to the US as adults and were therefore likely to have received most of their education elsewhere. The individual data reveal that 86% of immigrants who are over 25 years old and arrived within the last 6 years have attained levels of education that exceed the mean in their origin country. Those who come to the US, even as adults, appear to have higher educational achievement than those left behind.

As already discussed, it is likely that in addition to the rationing rule, supply side considerations enter. Obtaining permission to reside in the United States may be more easily acquired by those who are the most educated, given that slots are rationed. This pushes in the direction of getting the top immigrants from any given country, as assumed.

Additionally, Hanson, Liu, and McIntosh (2017) find that even for Mexico, which supplies the largest number of migrants to the US and which also is the largest source of unskilled labor, those who come to the United States are drawn from middle-income Mexicans, not from the lowest part of the income distribution. Grogger and Hanson (2015) find selective preference for staying in the US among foreign students in the US who have more educated parents and merit-based financial support. Again, this is a supply-side justification for the assumption that selection ends up being from the top of the distribution. Docquier, Lohest, and Marfouk (2007) pay explicit attention to "brain drain" from developing countries to more advanced places and document this, noting in particular that it has increased over time. Selection from the top is the recipient country's description of what the origin country calls brain drain.

Finally, it is possible to modify the model slightly to account for different aspects of policy. For example, in the US, skills and employment reasons account for about 15% of those awarded permanent residency each year. Suppose that all of those are from the top of the distribution, and those admitted for other reasons are less likely to be drawn from the top, with a lower conditional expectation of attainment. To the extent that the proportions of admission by reason could be measured by country of origin, this could be accommodated. The results on I_i still entering negatively in columns 3 and 4 of table 5 provide some support for the view that the proportion admitted on the basis of skill varies by country, as does the discussion of unauthorized immigration below.

Family Reunification and Undocumented Immigrants

The countries most likely to have immigrants who come in on a family reunification basis, with a few exceptions,[15] are those that have the largest number already in the US. They may bring the average level of education down, not because there are so many of them, but because they are selected on family basis, rather than skill. Although possible and probably true to some extent, the relationships predicted by the propositions and corollaries hold whether the

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[14]Chiswick and Miller (2011) argue that there is some negative assimilation that occurs after migration and Chiswick and Miller (2012) investigate both negative and positive assimilation.

[15]El Salvador is a good example, being over-represented by a factor of 32.

high immigrant countries, which also account for much of family reunification, are included or not.

Related, countries that are geographically close to the United States and over-represented, like Mexico and El Salvador, may have a higher proportion who enter without visas. Supply considerations are more likely to be a factor for these individuals because they are not subject to the immigration slot rationing system. It is also conceivable, although not obvious, that undocumented entrants would be of lower educational attainment than those who come in on the basis of family reunification, which is high among immigrants from those countries.

Passel and Cohn estimate the number of "unauthorized" immigrants by region of the world from which they migrated.[16] Those estimates can be used as an additional independent variable to determine whether countries in regions with a larger number of people in the US without authorization have lower attainment.

They do. The Passel and Cohn number of unauthorized immigrants from the region is added as a variable to the specification in table 1, column 1, and a significantly negative effect is found (the coefficient is -.00022 with a standard error of .00004). The estimate implies that a one standard deviation increase in the number in the US without authorization implies about two-thirds of a year less educational attainment among immigrants. Also, the coefficient on I_i falls from -.52 to -.40, which is consistent with the view that those who are in the US without documentation are less educated. But the main predictions of the model and theory are maintained, changing only slightly and not qualitatively. Attainment falls with the number of immigrants from a country and rises with both the population of that country and its average education.

Why Aren't Supply-based Explanations Sufficient?

Consider a pure supply theory of migration where those who get the most out of migrating move to the United States. There are a variety of versions of this, with the earliest being that of Sjaastad (1962). Already mentioned is the well-known work of Borjas (1987), which formalizes and applies the Roy (1951) model to migration.[17]

If origin-country-specific factors and rationing were not relevant, then there would be a supply determined A* that would be world-wide. Whether a Sjaastad or Roy-style model determined the desire to migrate, absent country-specific idiosyncracies, one would expect that there would be a level of ability such that those above that cutoff level found it worthwhile to

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[16]Passel and Cohn, "As Mexican share declined, U.S. undocumented immigrant population fell in 2015 below recession level" Pew Research Center, 2017.

[17]Grogger and Hanson (2011) find some support for the wage differential model driving selection of immigrants into a country. In particular, because there is a large difference between wages of high and low- skilled immigrants in the US, skilled immigrants tend to prefer the US as a destination country. What seems most relevant is the difference between the wages of the skilled in the destination country and the origin country, but this is likely to be correlated with the destination country's skill premium.

migrate and those below did not.[18] Under these circumstances, there would be no implied negative relation between the number from any country and average attainment in the US. In fact, it would likely go in the opposite direction from that predicted by this model and found in the data. Consider two countries of the same size. Given the same cutoff A*, if country A sends more migrants for reasons of supply to the US than does country B, then there must be a fatter upper tail in country A than in B, which would generally imply that the expected attainment of those from A would exceed that of those from B. But the reverse is true. The higher is I_i, the lower is the attainment of immigrants from i.

The role for supply emphasized here is in having the most able fill whatever quota is set by policymakers. Of course, the reality is that characteristics do vary by country potentially causing the cost of or benefits from migration to be higher in some origin countries than others. This might result in countries sending differing numbers and average attainments of migrants. This possibility has already been addressed in previous sections and analyzed in table 6, but it is worth considering the argument more specifically in this context.

Allowing costs to differ by country of origin is analogous to the gravity models used in trade economics[19]. Countries tend to trade more with their closest neighbors. Analogously, individuals are more likely to move closer to neighbors than to more distant ones. It is surely true that a migration version of gravity models explains some of the migration pattern. When countries are ranked by their representation ratios, nine of the top ten are from the Western Hemisphere. Without exception, these are countries with small populations, the largest being El Salvador with about 6 million people. However, as already discussed in detail above, distance is not a good predictor of the number of immigrants in the US. Recall that there is no significant correlation between distance of a country from the US and the number of immigrants from that country. Nor is distance a consistent factor in explaining attainment in the US, as shown in table 6. Distance matters in some specifications in table 6, but not in others. A couple of additional points are relevant.

First, from a supply point of view, it is the gain from migration, not the final attainment, that should be related to the desire to migrate. As a consequence, it is necessary to argue that those who attain the highest levels of education in the US also have the most to gain from migration, given the costs. This is not an obvious proposition because those with highest levels of education are scarce in their origin countries and might be particularly valuable there. Still, it is not unreasonable that the value of education in a highly developed economy may well be greater than the value in a less developed one.

Second, factors that are most likely to affect supply do not consistently explain attainment in the US, again using evidence on country growth rates, share in agriculture and GDP per capita as reported in table 6. More important, those factors do not even explain the number of immigrants from a given country. When the number of immigrants from a given country is regressed on potential supply determinants, which include GDP per capita, origin

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[18]If unskilled rather than skilled labor had a comparative advantage in US, then the reverse would be true. Those with ability below some A* would migrate and those above would not.

[19]See, for example, Bergstrand (1985) and Lewer, and Karemera, Oguledo and Davis (2000) and Van den Berg (2008), the latter two of which are direct applications to immigration.

country growth rate, share in agriculture and distance from the US with a control for country size, none is significant. Similarly, regressing I_i / N_i on the same variables (omitting N_i) finds no significant relationships, except distance. This suggests that supply alone does not do well in explaining the pattern of migration from the various source countries.

Patterns of Migration to Other Countries Refutes Simple Supply Explanations

Can there be any doubt that immigration policy affects migration flows? If a desirable destination country with an excess supply of potential immigrants decides for political reasons to let in more people from a given source country, there will be more from that country. Evidence from a comparison between the US, Canada and Sweden makes that clear.

Canada and the United States[20] are contiguous. Canada has an economy that is highly integrated and quite similar to that of the US. A migrant who finds the US a favorable economy relative to his or her origin country is likely to find Canada favorable as well. Were relative skill rewards or distance the major determinant of migration patterns, the countries that supply immigrants to the US would be similar to those supplying immigrants to Canada. Indeed, there is some similarity.[21] The correlation between immigrants from country i to the US and from country i to Canada is .31 across 120 origin countries. Supply surely matters and those whose skills are not highly valued in their home countries are more likely to choose those countries whose economies are favorable to those skills. If the US is favorable relative to the home country, in most cases, so too would be Canada. A positive correlation is consistent with that view, but a correlation of .31 means an r-squared of .09. In logs, however, the r-squared is around .4, which is a better indicator of the cross-country correlations. There is clearly significant correlation between migration patterns to the US and Canada from other source counties, but a large fraction of the variance remains unexplained. [22]

More specifically, there are large deviations in the patterns of migration that belie a simple supply explanation. Six of the top ten immigrant source countries to the United States are not among the top ten source countries to Canada. Most important, Mexico, the country that comprises four times as many immigrants in the US as any other country, is not even among the top 10 source countries of immigrants in Canada, despite Mexico being closer to Canada than

[20]Migrants moving to different parts of the US face greater differences in travel than some who contemplates a move to Canada instead of the US. The distance from Beijing to Vancouver, British Columbia is 4600 miles, virtually identical to the distance from Beijing to Seattle, Washington. The distance from Beijing to Washington, DC. is 6927, considerably further than that to Seattle even though both are in the US.

[21]The findings are based on data from http://www12.statcan.gc.ca/census-recensement/2016/dp-pd/hlt-fst/imm/Table.cfm?Lang=E&T=21&Geo=01&SO=4A, "Immigration and Ethnocultural Diversity Highlight Tables - Immigrant population by place of birth, period of immigration, 2016 counts, both sexes, age (total), Canada, 2016 Census — 25% sample data."

[22]Some variation and clustering is to be expected even without constraints on migration. For example, immigrants from Cuba are disproportionately found in Florida, even though they are free to move between states in the US.

any origin country other than the US.[23] This almost certainly reflects immigration policy. A large proportion of those from Mexico who come in to the US do so on this basis of family reunification. Because there are many Mexicans in the US already, those from Mexico are more likely to have relatives in the US (even given the population) relative to those from other countries.

Consider another important example. Hong Kong ranks fifth as a source of immigrants in Canada and is over-represented among Canadian immigrants by a factor of 29. Part of this is a reflection of Canada's decades long policy of attempting to attract migrants who are entrepreneurs and investors. By contrast, Hong Kong ranks 30th in sources of immigrants to the US. Other differences are difficult to explain on the basis of supply. The United Kingdom is the source country for eight times as large a proportion of Canadian immigrants as of US immigrants. The Canadian point system (in effect since 1967) favors language skills and education, which, in addition to family reunification, helps those from the UK migrating to Canada to a larger extent than those migrating to the US. Those from Cuba rank sixth in number of immigrants in the US and sixtieth in Canada. The migration to the US reflects a flood of refuges who came when Castro came to power. Florida is closer to Cuba than is Toronto, but the largest group of immigrants in Canada come from India, which is half way around the world. The US created special provisions for those fleeing a communist nation that allowed migration from Cuba to the US on humanitarian grounds.[24] Additionally, the US has almost 1 million immigrants from El Salvador, a country of 6 million, which means that a large fraction of Salvadorans have a relative in the US that make them eligible for entry on family grounds. Salvadorans are four times as over-represented among immigrants in the US than they are among immigrants in Canada. Family reunification policy in the US that favors Salvadorans is a more plausible explanation than that the US has a labor market much better suited to Salvadorans than does Canada.[25]

Analysis of Swedish data helps distinguish between supply and rationing explanations of migration and immigrant attainment. Like the US, Sweden does not base its immigration primarily on skill. Other factors are important in determining the composition of migrants to Sweden, but the factors in Sweden are somewhat different from those in the US. Sweden accepts immigrants on the basis of refugee status to a much greater extent than does the US. Other than the Scandinavian countries and countries related to them through history, like Iceland, the most over-represented origin countries for immigrants in Sweden are Bosnia, Lebanon, Somalia, Eritrea, and Iraq, which are countries with many fleeing from war.

Data were obtained from the Swedish Registry administrative data (Statistics Sweden)

[23]There are some small Caribbean countries that are closer to some parts of Canada than are some places in Mexico to other parts of Canada.

[24]Migration Policy Institute (2017).

[25]The fact that Spanish is prevalent in the US is a consequence of migration policy, not a factor that initially made the US a desirable location for Latinos.

and Registret över befolkningens utbildning.[26] The underlying dataset is similar to the ACS for the US and covers years 2011-2015 as in the US. Table 7 reports results.

First, columns 1 and 2 of table 7 repeat for Sweden the analysis done for the US in table 1. The dependent variable is average educational attainment in Sweden of immigrants from country i. The only change in independent variables is that I_i used is the number of immigrants from country i in Sweden, rather than in the US. Just as for the US, the number of immigrants from a country has a strong negative effect on educational attainment, whereas population and education of the origin country have strong positive effects on educational attainment. Important is that the negative effect of number of immigrants from country i is based on completely different countries in Sweden than it is in the US. It is implausible that such different migration patterns to the US versus Sweden occur as a result of supply conditions that differ. Because the economies of the US and Sweden are not so different particularly as compared with the economies of the primary origin countries to each, only geography would differ. But Sweden has more Iraqis and Somalis relative to the US because Sweden chose to let them in as an explicit refugee policy, not because it is easier (if in fact it is) to get from Iraq and Somalia to Sweden than to the US. It is highly unlikely that Iraqis and Somalis find it so much better to migrate to Sweden and Filipinos find it so much better to migrate to the US. Yet the effect of the I_i variable is qualitatively the same in Sweden as it is in the US, consistent with policy and rationing.

More generally, the correlation between the representation ratio in the US and that in Sweden is almost zero (.05) and between the number of immigrants in each of the two countries is also almost zero (.04). Were the same supply factors pushing migration, one would expect a much higher correlation between the pattern of migration to each of the two countries.

Column 3 of table 7 provides additional placebo-like evidence on this point. If supply were sufficient to explain migration patterns and attainment, then because the US economy is not so different from that of Sweden, one might expect the number who come to the US would be a good indicator of supply forces inducing those to come to Sweden as well. Thus, the number of immigrants in the US from country i is entered in column 3. It has no effect on attainment in Sweden, but the number of immigrants in Sweden from country i continues to matter. Even the educational attainment of immigrants from i in the US is not a very strong predictor of attainment of immigrants in Sweden as seen in column 4, and again, the number of immigrants from country i in Sweden remains a negative factor, albeit on the margin of significance.

Reverse Causation

[26]The Swedish dataset contains statistics for 98 countries (including Sweden) between the years 2011 and 2015. The number of observations included for each year are as follows: 5,472,582 (2011); 5,499,465 (2012); 5,528,680 (2013); 5,568,916 (2014); and 5,605,685 (2015). Immigrants account for about 19% of the sample. The earnings and transfer values refer to individuals betweens the ages 20 and 64, while the education values refer to individuals between the ages of 25 and 64. All variables come from register data (administrative sources) by Statistics Sweden and therefore cover all individuals who were registered in Sweden each particular year. All variables associated with education level come from Statistics Sweden's *Registret över befolkningens utbildning* or "Register of Population Education."

The primary implication of the model is that those countries that provide a large number of migrants to the US have lower educational attainment. The assumption is that the policy choice is on the number selected from country i and not the educational attainment level itself. But suppose the US had an explicit policy of letting in only low-skilled individuals, say to prevent competition with the higher skilled native-born Americans, and to implement the policy, let in more from low-skilled countries.

First, μ_i, which measures education in the origin country, should control for this factor. If the US is intentionally admitting those from low skilled countries, μ_i would be lower on average among the immigrant population, but including μ_i as an explanatory variable should leave no room for I_i or N_i to influence average attainment among immigrants. Still, it is worth exploring the reverse causation more directly.

The best evidence against this view is provided by the simple correlation of I_i and μ_i, which is essentially zero at -.02.[27] There does not seem to be any pattern of selecting more immigrants from countries with low levels of educational attainment.

Another possibility is that immigrants with low levels of education are more likely to be admitted to the United States on an individual basis. Although possible, there is no reason why this would result in a negative correlation between number from any particular country and average skill level. Low-skill immigrants might be selected, but there are plenty of low-skilled immigrants in the world and there is nothing that implies that the lowest skilled would all be from one country. Were this the case, randomly selected low skilled would come disproportionately from high population countries with many low skilled individuals. Specific examples, India being most important, runs counter to this view. India is the second most populous country in the world and has one of the lowest levels of education of the 134 countries. Yet Indians are both under-represented among immigrants in the US and highly educated. Given that the US allows in many Indians and given that there are many poorly educated Indians, if the policy were to select negatively on the basis of skill, one would expect that the Indians who are here would be of low skill. Indians in the US are highly educated because a small number of Indians are admitted relative to the Indian population. That selection rule is consistent with the results.

Furthermore, a policy that seeks low-skilled immigrants does not appear to be a true description of the data. The average educational attainment among immigrants in the sample as a whole is a little over 12 years, which is not much below that for the native-born American population.

Random Selection of Immigrants

The implications on I_i and N_i that form the basis of propositions 1 and 2 and corollaries 2 and 3 are a result of a model that assumes immigration slots are rationed on the basis of ability, from the top down. Were the selection process random, there would be no reason to expect that countries that were sources of a larger number of immigrants, I_i, would have lower levels of attainment. The same is true of population of the origin country. Were immigrants selected randomly, then the distribution of talent in the US would mimic that of the origin country. It is

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[27]It is -.004 when weighted by the number of immigrants from the country.

true that Proposition 3 and corollary 4, which postulate a positive correlation between origin country educational attainment and educational attainment of their US immigrants, could result from a random selection process because countries with higher levels of educational attainment would also send migrants with higher levels of education under random selection. The most important implications, however, are violated by the random selection model.

Dynamics and Individual Characteristics

The analysis to this point has examined only country level data, but the individual ACS data shed light on some details that are of additional interest. One issue is whether immigrants who enter when young have higher attainment levels than those who enter when old. Table 8 provides the answer.

In table 8, the raw ACS data are used to determine outcomes at the individual level, rather than for the country of origin, although country variables can be used as controls. There are approximately 1.5 million individual observations on which results are based. Note that because these are not country averages, but are instead individual data, wages and earnings are logged as is standard.

As before, the variables that are predicted by the model to matter (I_i, N_i and μ) continue to enter as predicted in the individual level regressions, even when individual characteristics are held constant as in columns 2 through 6. Not surprisingly, current age enters positively and age squared negatively for all attainment variables. Educational attainment, hourly wage and total annual earnings are related to age of entry negatively. Those who enter the US when young have higher levels of attainment than those who come in when older, and that result holds for all three attainment variables.[28] An interaction term between age of entry and average level of schooling in the origin country enters positively, mitigating the adverse affects of coming as an adult.[29] If the individual migrated from a high education country, there is less or no advantage to coming as a child. But if the immigrant migrated from a country with a low average level of education, final educational attainment, hourly wages and earnings are higher when coming young. This is likely to affect the positive differences in quality of education between the US and low education countries. That positive difference in quality is not present when the origin country has high average levels of education. Female immigrants have lower levels of earnings than their male counterparts, although educational attainment is approximately the same for male and female immigrants, with males having only .2 years advantage.

Cohorts

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[28]Quadratic terms did not enter any of the regressions in a meaningful way and were often statistically insignificant, even with regressions having almost a million to 1 ½ million obervations.

[29]Cohort effects were analyzed as well. Some countries' immigrants entered on average as early as the 1960s and some as late as the early 2000s. Holding other factors constant in table 8, the only attainment variable that is statistically and economically related to average year of entry is educational attainment. Those who entered from countries that reflect more recent waves of migration have higher levels of education. But they do not have substantially higher annual earnings or higher hourly wages, given their personal educational attainment.

The IPUMS data provide information on educational attainment of the source country for some countries and some decades used in the analysis of the ACS data. The data are incomplete, however. For example, IPUMS provides average levels of education in Mexico in 1960 but not for Cuba, when there was a large wave of Cuban migration and no information is provided at all for 63 of the 129 countries analyzed in table 1. Still, for those countries on which information is available, the attainment of immigrants can be based on the education in the source country, the population in the source country, and the number of immigrants from that country who came in during that same decade as the immigrant who is reflected in each particular observation. This provides a more accurate test of the theory because it is based on selection at the time of entry, i.e., the flow, rather than on the stock of immigrants from a country who are present now. The drawback is that not all countries can be analyzed because the IPUMS data and time periods only correspond to a subset of countries and individuals.

Table 9 repeats the analysis of table 1, 2, and 3 at the individual level for countries on which IPUMS data are available. The I_i variable used is the number of immigrants from country i who came in during the decade in which the individual in question entered. Analogously, the N_i and μ_i variables refer to the values that held at the time the individual in question migrated to the US. These are better measures of the variables described by the theory, but as said, they do not cover all countries.

Column 1 analyzes educational attainment using the individual-specific variables. Column 2 repeats the country level regression done in column 1, table 1 on the subset of countries for which data used in column 1 of table 9 are available for comparison.[30] Column 3 is analogous to column 1 of table 2 and column 4 repeats the country level table 2 analysis on the subset of IPUMS available countries. Similarly, column 5 is analogous to column 1 of table 3 and column 6 repeats the country level table 3 analysis on the subset of IPUMS countries. There are some substantial changes in magnitudes of the coefficients between the cohort-specific estimates and those that treat immigrants as a stock that arrived at the same time, but none that changes interpretation or contradicts the predictions of the model. Additionally, all of the results are qualitative identical to those shown in tables 1, 2, and 3. As before, the smaller the number of immigrants, the larger the population of the source country and the higher the average years of education in the origin country, the higher is expected attainment by the immigrant in the US. The quantitative effects in table 9 are in line with results in earlier tables. The refined cohort analysis on the subset of countries for which data are available does not alter any of the conclusions drawn from prior tables.

Conclusion

The larger the number of immigrants from a given country, the lower is the educational attainment, wage rates and earnings of that group. The pattern is a result of a selective immigration process that rations slots. Because of variations in the way the various origin countries are treated by the immigration system, a particular distribution of immigrants results,

[30] This is equivalent to the weighted version shown in table 1 on the subset of 66 countries because the data are at the individual level. Those countries with more individuals are weighted more heavily, exactly as in column 1, table 1, except that there are fewer countries used in table 9 than in table 1.

which gives rise to differences in educational attainment and earnings by country of origin. Those countries that are awarded the largest number of slots tend to have immigrants with lower attainment levels.

For the same reason, the larger the population of the origin country, the higher the attainment of immigrants from that country. It is easier to select one million highly educated people from India with 1.3 billion people than it is from Laos with 7 million people. Consequently, immigrants of Indian origin have higher levels of educational attainment than do immigrants of Laotian origin.

A model of selection is constructed that yields seven specific empirical implications, all of which are borne out by data from the American Communities Survey, 2011-2015. The larger the number of immigrants from an origin country, the lower the level of educational attainment, of wages and of earnings in the US. The larger the population of the origin country, the higher the educational attainment, the higher the wages and the higher the earnings of those immigrants in the US. A more parsimonious approach expresses predictions in terms of a representation ratio, which is a measure of how under- or over-represented a country is in the US immigrant stock. Immigrants from source countries that are over-represented are predicted and found to have lower attainment in education, wages and earnings. Data from Sweden support the hypotheses as well and yield results consistent with those from the US.

The theory also has implications for the difference between attainment of immigrants and that of the population in the origin country. This provides a separate test of the model and all implications are borne out. In particular, the larger is the stock of immigrants from any given country, the smaller is the difference between the attainment of immigrants from that country and that of the origin population. Additionally, the larger is the population of the origin country, the larger is the difference between the attainment of immigrants from that country and the origin population.

The model that gives a role to only these three variables explains 73% of the variation in country-mean educational attainment of immigrants in the US. A structural approach that assumes normality of the underlying educational distribution coupled with the model's specific selection rule performs well in explaining the data, yielding a goodness-of-fit statistic that is about 83% as high as the unconstrained reduced form version. Overall, the model that postulates selection from the top of origin countries' ability distribution does well in describing the actual data.

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Table 1: Attainment of U.S. Immigrants
Dependent Variable= Average Education of Immigrants from Country i

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I_i	-0.524***	-0.702***	-1.837***	-2.607***	-0.496***	-0.519***		
	(0.0333)	(0.153)	(0.288)	(0.495)	(0.0696)	(0.184)		
N_i	0.252***	0.283***	1.519***	1.189***	0.269***	0.289***		
	(0.0307)	(0.0683)	(0.193)	(0.203)	(0.0627)	(0.0824)		
μ_i	0.322***	0.265***	0.402***	0.291***	0.362***	0.399***	0.191**	0.250***
	(0.0528)	(0.0409)	(0.0364)	(0.0365)	(0.123)	(0.108)	(0.0796)	(0.0416)
R_i							-0.111***	-0.0451***
							(0.0167)	(0.01000)
Weight	I_i	None	I_i	None	I_i	None	I_i	None
Sample	Full	Full	Without Mexico, Philipp., India, China	Without Mexico, Philipp., India, China	$I_i > 0.2$	$I_i > 0.2$	Full	Full
Constant	10.248***	11.142***	9.428***	10.892***	9.689***	9.404***	11.456***	11.514***
	(0.493)	(0.377)	(0.372)	(0.349)	(1.172)	(1.031)	(0.701)	(0.379)
Observations	129	129	125	125	29	29	129	129
R^2	0.7276	0.3468	0.6311	0.4601	0.7614	0.5156	0.2775	0.3012

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Attainment of U.S. Immigrants
Dependent Variable = Average Hourly Full-Time Wage for Immigrants from Country i

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I_i	-1.801***	-2.454***	-6.681***	-8.162***	-1.646***	-1.873*		
	(0.154)	(0.835)	(1.561)	(2.955)	(0.319)	(0.949)		
N_i	1.327***	1.451***	5.997***	4.381***	1.388***	1.487***		
	(0.142)	(0.373)	(1.044)	(1.214)	(0.288)	(0.424)		
μ_i	1.748***	1.797***	2.150***	1.893***	1.716***	2.063***	0.606	1.491**
	(0.244)	(0.223)	(0.197)	(0.218)	(0.565)	(0.557)	(0.763)	(0.610)
R_i							-0.481***	-0.212**
							(0.151)	(0.102)
Weight	I_i	None	I_i	None	I_i	None	I_i	None
Sample	Full	Full	Without Mexico, Philipp., India, China	Without Mexico, Philipp., India, China	$I_i > 0.2$	$I_i > 0.2$	$I_i > 0.2$	$I_i > 0.2$
Constant	13.819***	14.898***	10.316***	13.948***	12.882**	10.475*	25.018***	17.990***
	(2.280)	(2.058)	(2.015)	(2.080)	(5.379)	(5.306)	(6.748)	(5.658)
Observations	129	129	125	125	29	29	29	29
R^2	0.6633	0.3805	0.5663	0.4133	0.6991	0.4809	0.2920	0.2967

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Attainment of U.S. Immigrants
Dependent Variable = Average Annual Earnings for Immigrants from Country i

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I_i	-2053.17***	-2890.98**	-9929.36***	-11081.17**	-1855.76***	-2203.01		
	(229.85)	(1223.88)	(2248.49)	(4334.64)	(477.97)	(1409.56)		
N_i	1622.04***	1805.71***	6676.43***	5539.12***	1652.19***	1785.27***		
	(211.60)	(546.54)	(1503.32)	(1780.99)	(430.58)	(629.99)		
μ_i	1098.23***	1359.01***	1735.91***	1495.76***	832.55	1532.07*	201.68	1248.30***
	(364.55)	(327.18)	(284.15)	(319.30)	(844.96)	(826.98)	(436.49)	(324.15)
R_i							-543.18***	-266.70***
							(91.84)	(77.83)
Weight	I_i	None	I_i	None	I_i	None	I_i	None
Sample	Full	Full	Without Mexico, Philipp., India, China	Without Mexico, Philipp., India, China	$I_i > 0.2$	$I_i > 0.2$	Full	Full
Constant	24155***	23837***	19485***	22614***	24943***	19889**	34348***	26587***
	(3400.98)	(3017.14)	(2902.10)	(3050.82)	(8050.29)	(7879.50)	(3844.90)	(2951.03)
Observations	129	129	125	125	29	29	129	129
R^2	0.5325	0.1788	0.3689	0.2080	0.5808	0.3015	0.2174	0.1691

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Attainment of U.S. Immigrants as Compared with Natives of Origin Country

	(1) IV	(2) OLS
Dependent Variable	Delta	Delta
I_i	-0.499***	-0.558***
	(0.0528)	(0.0416)
N_i	0.338***	0.206***
	(0.0636)	(0.0403)
μ_i	-0.286	-0.765***
	(0.182)	(0.0838)
$Tertiary_i$		
Weight	I_i	I_i
Sample	Full	Full
Constant	6.623***	11.356***
	(1.815)	(0.855)
Observations	70	70
R^2	0.7993	0.8618

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Attainment of Immigrants in U.S.
Dependent Variable = Average Education Level of Immigrants from Country i

	(1)	(2)	(3)	(4)	(5)	(6)
R_i	-0.111***	-0.0451***	-0.0448***	-0.0369***		
	(0.0167)	(0.01000)	(0.0106)	(0.00933)		
μ_i	0.191**	0.250***	0.310***	0.267***	0.275***	0.304***
	(0.0796)	(0.0416)	(0.0497)	(0.0387)	(0.0550)	(0.0349)
I_i			-0.481***	-0.628***		
			(0.0329)	(0.146)		
N_i			0.215***	0.244***		
			(0.0301)	(0.0654)		
$\ln(I_i)$					-1.374***	-0.643***
					(0.0869)	(0.0811)
$\ln(N_i)$					0.946***	0.545***
					(0.0888)	(0.0609)
Weight	I_i	None	I_i	None	I_i	None
Sample	Full	Full	Full	Full	Full	Full
Constant	11.456***	11.514***	10.714***	11.333***	10.136***	10.274***
	(0.701)	(0.379)	(0.476)	(0.360)	(0.468)	(0.355)
Observations	129	129	129	129	129	129
R^2	0.2775	0.3012	0.7617	0.4201	0.6801	0.5342

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Attainment of Immigrants in U.S.
Dependent Variable = Average Education Level of Immigrants from Country i

	(1)	(2)	(3)	(4)
I_i	-0.319***	-0.500***	-1.430**	-2.447***
	(0.0501)	(0.150)	(0.630)	(0.780)
N_i	0.160***	0.179**	0.959**	1.185***
	(0.0383)	(0.0686)	(0.361)	(0.336)
μ_i	0.445***	0.358***	0.563***	0.399***
	(0.125)	(0.104)	(0.115)	(0.0954)
GDP per Capita (PPP Adjusted)	0.0309	0.0141	-0.00145	0.0143
	(0.0217)	(0.0170)	(0.0200)	(0.0156)
GDP Growth Rate	-0.117**	0.0418	0.0703	0.0872*
	(0.0564)	(0.0467)	(0.0571)	(0.0437)
Agricultural Value Added as % of GDP	0.160***	0.0573	0.0793*	0.0422
	(0.0504)	(0.0353)	(0.0450)	(0.0321)
Distance between Washington DC and capital of country i	0.273***	0.151**	0.0652	0.00131
	(0.0704)	(0.0730)	(0.0823)	(0.0778)
Weight	I_i	None	I_i	None
Sample	Full	Full	Without Mexico, Philipp., India, China	Without Mexico, Philipp., India, China
Constant	6.788***	8.762***	7.027***	9.036***
	(1.277)	(1.094)	(1.147)	(1.016)
Observations	69	69	65	65
R^2	0.8797	0.4629	0.5793	0.5042

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Analysis of Sweden
Dependent Variable: Proportion with post-secondary degree

	(1)	(2)	(3)	(4)
$I_{i\ \text{Sweden (in millions)}}$	-0.801**	-2.11***	-0.766**	-0.670*
	(0.348)	(0.558)	(0.349)	(0.347)
$N_{i\ \text{(in 100 millions)}}$	0.205***	0.213***	0.149**	0.109
	(0.0437)	(0.0498)	(0.0677)	(0.0697)
μ_i	0.0189***	0.0256***	0.0184***	0.0145***
	(0.00423)	(0.00396)	(0.00424)	(0.00465)
$I_{i\ US}$			0.00000110	0.00000142
			(0.00000102)	(0.00000101)
$A_{i\ US}$				0.0210*
				(0.0110)
Weight	$I_{i\ \text{Sweden}}$	None	$I_{i\ \text{Sweden}}$	$I_{i\ \text{Sweden}}$
Constant	0.102**	0.0957**	0.0975**	-0.157
	(0.0445)	(0.0402)	(0.0446)	(0.140)
Observations	77	77	77	77
R^2	0.397	0.482	0.406	0.435

Standard errors clustered at the area level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Attainment of U.S. Immigrants (Individual level data)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Education Attained in Years	Education Attained in Years	Natural Log of Hourly Earnings	Natural Log of Annual Earnings	Education Attained in Years Origin Country Average
I_i	-0.524***	-0.586***	-0.0277***	-0.0293***	-0.524***
	(0.00106)	(0.00103)	(0.000260)	(0.000337)	(0.0333)
N_i	0.252***	0.274***	0.0251***	0.0270***	0.252***
	(0.000974)	(0.000945)	(0.000220)	(0.000285)	(0.0307)
μ_i	0.322***	0.234***	-0.0000175	-0.00996***	0.322***
	(0.00168)	(0.00317)	(0.000757)	(0.000982)	(0.0528)
Age		0.0367***	0.0477***	0.102***	
		(0.00133)	(0.000449)	(0.000581)	
Age^2		-0.000867***	-0.000394***	-0.000982***	
		(0.0000121)	(0.00000470)	(0.00000609)	
Age of Arrival to U.S.		-0.0905***	-0.0188***	-0.0253***	
		(0.000997)	(0.000265)	(0.000343)	
Age of Arrival to U.S. x μ_i		0.00714***	0.00111***	0.00151***	
		(0.000109)	(0.0000292)	(0.0000379)	
Female		-0.243***	-0.235***	-0.470***	
		(0.00684)	(0.00156)	(0.00202)	
Education Attained in Years			0.0634***	0.0746***	
			(0.000197)	(0.000256)	
Constant	10.248***	12.521***	1.120***	7.436***	10.248***
	(0.0157)	(0.0426)	(0.0122)	(0.0158)	(0.493)
Weight	None	None	None	None	None
Sample	Full	Full	Full	Full	Full
Observations	1491182	1491182	981178	981178	1491182
R^2	0.1816	0.2422	0.2111	0.2033	0.7276

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9
Cohort Analysis
(decade specific in columns 1, 3, 5; current stock measures of variables in 2, 4, 6)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Education attainent	Education (at origin country level)	Hourly Wage	Hourly Wage (at origin country level)	Annual Earnings	Annual Earnings (at origin country level)
Ii	-0.369***	-0.509***	-1.217***	-1.476***	-1,655***	-1,883***
	(0.00126)	(0.000369)	(0.0208)	(0.00263)	(14.42)	(2.610)
N_i	0 .274***	0.182***	1.161***	1.139***	1,944***	1,433***
	(0.00141)	(0.000280)	(0.0232)	(0.00187)	(16.14)	(1.983)
μ	0.394***	0.137***	0.663***	1.283***	1,366***	767.9***
	(0.00253)	(0.000657)	(0.0431)	(0.00464)	(29.11)	(4.652)
Constant	10.42***	12.31***	23.33***	20.36***	25,878***	28,904***
	(0.0161)	(0.00447)	(0.277)	(0.0316)	(185.1)	(31.68)
Observations	773,960	773,960	545,182	374,772	773,960	773,960
R-squared	0.186	0.800	0.013	0.725	0.043	0.643

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A

Proofs

Proposition 1:
From (1), using the implicit function theorem,

$$\frac{\partial A_i *}{\partial I_i} = -\frac{\partial / \partial I_i}{\partial / \partial A_i *}$$

$$= \frac{-1}{N_i f_i (A_i *)}$$

which is negative.

Note also that in (3), $\left[\frac{\int_{A_i *}^{\infty} A f_i (A) dA}{1 - F_i (A_i *)} - A_i * \right]$ is just the conditional expectation of A, given $A > A_i *$, minus $A_i *$, which is necessarily positive since the conditional expectation must exceed its lower limit. This implies that the sign of the first term in (3) is just the sign of $\partial A_i * / \partial x$.

Additionally, when the underlying distribution of ability, $f_i(A_i *)$, is independent of x as it is for $x = I_i$, the sign of the derivative in (3) is the same as that of $\partial A_i * / \partial x$ because the second term is zero.

Thus, since $\partial A_i * / \partial I_i < 0$, $\overline{A}_i$ decreases in I_i . |||

Proposition 2:

Analogously,

$$\frac{\partial A_i *}{\partial N_i} = -\frac{\partial / \partial N_i}{\partial / \partial A_i *}$$

$$= \frac{1 - F_i (A_i *)}{N_i f_i (A_i *)}$$

which is positive. By the same logic that is in the proof above, and since $f_i(A)$ does not depend on N_i,

$$\frac{\partial \overline{A}_i}{\partial N_i} > 0 . \qquad |||$$

Proposition 3:

First note that when $F_i(A) = F(A - \mu_i)$,

$$\frac{\partial A_i *}{\partial \mu_i} = -\frac{\partial / \partial \mu_i}{\partial / \partial A_i *}$$

$$= \frac{N_i f (A_i * - \mu_i)}{N_i f (A_i * - \mu_i)}$$

$$= 1$$

from (1).

Substituting into (3) yields

$$\frac{\partial \overline{A}_i}{\partial \mu_i} = \frac{f_i(A_i * - \mu_i)}{1 - F(A_i * - \mu_i)} \left[\frac{\int_{A_i *}^{\infty} A f_i(A) dA}{1 - F_i(A_i *)} - A_i * \right]$$

$$+ \frac{1}{1 - F(A_i * - \mu_i)} \int_{A_i *}^{\infty} A \frac{\partial f(A - \mu_i)}{\partial \mu_i} dA$$

The first term is positive because, as stated before, the conditional expectation exceeds its lower limit. The second term is positive because

$$\frac{\partial f(A - \mu_i)}{\partial \mu_i} = -f'(A - \mu_i)$$

and because f '(A) <0 for $A > A_i*$. |||

Corollaries

The proofs of the corollaries follow.

Corollary 1:

Rewrite (1) as

$$[1 - F_i(A_i *)] - R_i \frac{\sum_i I_i}{\sum_i N_i} = 0$$

Then

$$\frac{\partial A_i *}{\partial R_i} = \frac{\frac{-\partial}{\partial R_i}}{\frac{-\partial}{\partial A_i *}}$$

$$= \frac{-\sum_i I_i / \sum_i N_i}{f_i(A_i *)}$$

which is negative. Using the same logic as in the proof of proposition 1 and noting that $F_i(A)$ does not depend on R_i,

$$\frac{\partial \overline{A}_i}{\partial R_i} < 0$$ |||

To prove the corollaries that relate to Δ, note that for any variable x,

$$\frac{\partial \Delta}{\partial x} = \frac{f_i(A_i^*)\dfrac{\partial A_i^*}{\partial x}}{[1-F_i(A_i^*)]}\left[\frac{\int_{A_i^*}^{\infty} Af_i(A)dA}{1-F_i(A_i^*)} - A_i^*\right]$$

$$+\frac{1}{1-F_i(A_i^*)}\int_{A_i^*}^{\infty} A\frac{\partial f_i(A)}{\partial x}dA$$

$$-\int_{-\infty}^{\infty} A\frac{\partial f_i(A)}{\partial x}dA$$

Corollary 2:

Since $F_i(A)$ does not depend on I_i and since $\dfrac{\partial A_i^*}{\partial I_i} = \dfrac{-1}{N_i f_i(A_i^*)}$,

$$\frac{\partial \overline{A}_i}{\partial I_i} = \frac{f_i(A_i^*)\left[\dfrac{-1}{N_i f_i(A_i^*)}\right]}{[1-F_i(A_i^*)]}\left[\frac{\int_{A_i^*}^{\infty} Af_i(A)dA}{1-F_i(A_i^*)} - A_i^*\right] < 0$$

|||

Corollary 3: Since $F_i(A)$ does not depend on N_i and since $\dfrac{\partial A_i^*}{\partial N_i} = \dfrac{1-F_i(A_i^*)}{N_i f_i(A_i^*)}$, which is positive,

$$\frac{\partial \overline{A}_i}{\partial Ni} = \frac{f_i(A_i^*)\left[\dfrac{1-F_i(A_i^*)}{N_i f_i(A_i^*)}\right]}{[1-F_i(A_i^*)]}\left[\frac{\int_{A_i^*}^{\infty} Af_i(A)dA}{1-F_i(A_i^*)} - A_i^*\right] > 0$$

|||

Corollary 4:

Consider two countries. Define the base country as having an ability distribution given by F(A) and arbitrary country i as having an ability distributions $F_i(A)$, where as in the text, $F_i(A)$ is a displacement of F(A) by μ_i.

The cutoff level for the base country is A* to satisfy (1) such that

N_0 [1-F(A*)] = I_0

where I_0 is the policy determined number of immigrants from the base country.

Recall that

$$\frac{\partial A_i *}{\partial \mu_i} = 1$$

so that $A_i^* = A^* + \mu_i$. The goal is to show that Δ is invariant with respect to μ. This is equivalent to showing that average ability among immigrants, $\overline{A}_i$, is greater than $\overline{A}$ by μ_i because

$$\begin{aligned}
&\Delta_i = \overline{A}_i - E(A_i) \\
&\Delta = \overline{A} - E(A) \\
&and \\
&E(Ai) - E(A) = \mu_i \\
&so\,if \;\; \Delta_i = \Delta, \\
&then \\
&\overline{A}_i - \overline{A} = \mu_i
\end{aligned}$$

Definitionally,

$$\overline{A}_i = \frac{1}{1 - F_i(A_i *)} \int_{A_i *}^{\infty} A f_i(A) dA$$

or

$$\overline{A}_i = \frac{1}{1 - F(A*)} \int_{A* + \mu_i}^{\infty} A f(A - \mu_i) dA$$

because $F_i(A) = F(A-\mu_i)$, $f_i(A) = f(A-\mu_i)$ and $A_i^* = A^* + \mu_i$.

A change of variables allows this to be rewritten as

$$\begin{aligned}
\overline{A}_i &= \frac{1}{1 - F(A*)} \int_{A*}^{\infty} (A + \mu_i) f(A) dA \\
&= \frac{1}{1 - F(A*)} \int_{A*}^{\infty} A f(A) dA + \frac{\mu_i}{1 - F(A*)} \int_{A*}^{\infty} f(A) dA \\
&= \frac{1}{1 - F(A*)} \int_{A*}^{\infty} A f(A) dA + \frac{\mu_i [1 - F(A*)]}{1 - F(A*)} \\
&= \overline{A} + \mu_i
\end{aligned}$$

Appendix B

Additional Tables

Table B-1

Variable	Description	Source	Mean	Std Dev
A_i (Education)	Mean years of schooling among immigrants from country i	ACS	13.32207	1.641941
A_i (Hourly Wage)	Mean wage among immigrants from country i (condition on working)	ACS	27.79516	7.738721
A_i (Annual Earnings)	Mean earnings among immigrants from country i (unconditional)	ACS	33062.38	10567.58
I_i	Number of immigrants in US from country i in millions	ACS	0.23	0.75
N_i	Population of country i in 100 millions	World Bank Database 2015	0.53	1.71
μ_i	Mean schooling in country i	UN Development Reports 2016	8.611628	2.796416
R_i	Representation ratio	Created	6.279349	12.64804
$Tertiary_i$	Percentage with tertiary education in country i	Barro and Lee	10.6199	6.762148
$GDP/person_i$	Per capita GDP in purchasing power parity dollars	Heston and Summers	18071.52	13331.35
GDP $growth_i$	5 year growth rate of GDP	Heston and Summers	3.774583	3.437578
Agr share in GDP_i	Agricultural output / total output in country i	World Bank	6.976657	6.589
μ_i Sweden	Proportion with tertiary education in Sweden	Registret över befolkningens utbildning	0.3	0.13
I_i Sweden	Number of immigrants in Sweden from country i	Swedish Registry	11311	17695
μ_i (decade specific measure)	Average educational achievement	IPUMS	5.308946	2.000397
sd (decade specific measure)	Standard deviation of educational achievement	IPUMS	3.965702	0.5955079
p90 (decade specific measure)	90^{th} percentile of educational achievement	IPUMS	10.66928	2.622574
N_i (decade specific measure)	Country population	IPUMS	204379977.48	359734697.88

Appendix C

$F_i(A_i^*)$ is assumed to be a normal distribution, with mean μ_i and standard deviation σ_i for country i. Define the cumulative standard normal as $G(z_i)$ with $z_i = (A_i^* - \mu_i) / \sigma_i$. Because I_i is in millions and N_i is in 100 millions, it is necessary to convert N_i into the same units so define

$N_i^* \equiv 100$ Ni .

$$Ni^*[\ 1- G(\ z_i)\ ] = I_i$$

or

$$G(z_i) = 1- I_i / N_i^*$$

Thus,

$$z_i^*= G^{-1}(1- I_i / N_i^*)$$

where z_i^* is the A_i^* cutoff converted into standardized normal units.

Then,

$$A_i^* = \sigma_i\, G^{-1}(1- I_i / N_i^*) + \mu_i \qquad \text{(C1)}$$

which is easily obtainable.

Once A_i^* is obtained from (C1), it is possible to estimate A_i. That is done as follows. Because A_i^* is in the upper tail of the normal for all countries (even Mexicans at about 7 million equal only about 6% of Mexico's population at the time of the sample), the tail of the distribution is flat, close to linear, and negatively sloped. Also, because A_i^* is so high relative to μ_i, it is assumed that

$$E(A_i \mid A_i > A_i^*) = \quad A^*+k$$

Given the highly irregular country-specific histograms for the educational distributions, particularly in the upper tails, this assumption provides some robustness to the estimates. It essentially allows A_i^* to do all the work, but A_i^* incorporates the origin country-specific information on mean education, standard deviation of education and selects A_i^* so as to ensure that the upper tail corresponds to I_i / N_i .

Because the standard deviations are available for only 66 of the 129 countries, the reduced form specification estimated in column 1, table 1 is repeated for the 66 countries. Coefficients are similar as is the r-squared, which rises slightly to .75.

Goodness of fit of the structural model is calculated by regressing the actual A_i on the predicted A_i across all i countries. The r-squared is .62, meaning that the structural model fits about 83% as well as the reduced form version, lending additional credence to the approach formalized through equations (1) and (2).

Appendix D

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