Are Mexican migrants to the US adversely selected on ability?[1]

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Version date: March 7, 2008

[1] We thank Yana Rodgers, George Grayson, David Card and David Jaeger for helpful comments and Dheeraj Jagadev and Shannon White for capable research assistance. Contact author is Eric Jensen (eric_jensen@wm.edu)

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Abstract

Recent migrants to the United States have displayed lower earnings levels and a slower rate of earnings convergence with natives than previous immigrants. Borjas has argued that this reflects adverse selection of immigrants; others, including Card, Chiquiar and Hanson, and Duleep and Regets, question this contention. Some of the ambiguity may be due to measurement problems, with educational attainment (or its labor market consequences) used in place of unobserved migrant quality. Using Mexican Migration Project data, we estimate models of migration and employment. Our results suggest that educational attainment is not a good indicator of ability, since much of the observed national-level variation in educational attainment in Mexico appears to be the result of local constraints in the supply of education. We propose an alternative measure of migrant quality that incorporates education supply constraints, and present evidence of Mexican emigrants self-selecting positively on ability.

Are Mexican migrants to the US adversely selected on ability?

In an influential body of work, Borjas (1990, 1991, 1994, 1999) has extended the Roy (1951) model of endogenous selection to analyses of migration, where the choice actors make is country of residence (effectively a basket of occupations and earnings), and the model is applied to international migration to the United States. Borjas' assumption, after Roy, is that placement within an income distribution is reflective variously of ability, skills or "ethnic capital." Borjas (1994) defines ethnic capital conceptually as the quality of the ethnic environment in which a person is raised and operationally as the average educational attainment in a sending country. He posits that this ethnic capital influences the skills and labor market outcomes of the children of immigrants, and suggests that the difference in US earnings between immigrants and natives is useful as a proxy for relative skill differentials. In this setting, even if mean incomes in both countries were the same, Roy's well know result is that those in the left tail of the relatively diffuse Mexican income, ability, or skills distributions would have an incentive to migrate to the relatively egalitarian United States.

In later work of Borjas and in work of other contributors to this literature, discussion centers on the placement of migrants within the distribution of skills, with special regard for the transferability of skills acquired in the sending country. This discussion is couched in human capital terms. Duleep and Regets (1999), for example, predict that those with more to gain in investing in human capital, including migrating, will do so. This is partly driven by low opportunity cost and partly by high expected benefits of migrating. Their empirical prediction is that earnings will grow faster for immigrants than for the native born. Schoeni (1997) finds less reassuring evidence on this count. Chiquiar and Hanson (2005) compare counterfactual predictions of skill premia for US immigrants, had they remained in the Mexican labor market, with the actual distribution of US earnings. In contrast to Borjas, they find that Mexican immigrants would fall in the middle and upper portion of the Mexican wage distribution.

As Borjas points out, at issue is not just the pace of earnings growth, but the difference in initial earnings levels between immigrants and native-born populations. Following a narrow interpretation of Roy, the issue is the labor market skills of migrants. Assuming that training is provided efficiently in sending countries, the least able are also the least trained. They have chosen to accumulate little human capital because the net benefit to them is low. Borjas' policy recommendation to limit immigration (e.g., Borjas 1999) follows unavoidably.

Roy's is very much a story of functioning markets. However, in many developing countries, populations are substantially rural, while educational resources are heavily concentrated in urban areas. Educational supply constraints are more likely to bind in rural areas, causing levels of educational attainment in rural areas to be lower, all else constant. Interpreting educational differences across the population of migrants from a given sending country as reflective of broader quality differentials clearly is problematic, since some high-ability individuals from educationally supply-constrained rural areas may have low levels of educational attainment, compared to those from urban areas. The Borjas recommendation to limit low-skill immigrants carries less force in this case, as the tie between ability and presumptive measures of ability, such as educational attainment, is a noisy one. There may be substantial gains to the host society accruing from training those migrants who, due to supply constraints in sending countries, have low levels of human capital upon arrival but, because of their high ability levels, have relatively high expected gains from human capital accumulation.

We use data from the Mexican Migration Project to construct a model that accounts for potentially supply-constrained access to education within Mexico. We find that it is individuals better educated than their geographic peers but from impoverished, education-constrained regions of Mexico, rather than a broad cross-section of the less educated, who are most likely to migrate to the United States. The efficiency of exclusionary immigration policies based on the presumption of low migrant ability therefore appear to be of questionable efficiency vis-à-vis training or other more migrant-friendly policies that would allow the host country to capitalize on able but suboptimally trained migrants.

Negative or positive selection of immigrants?

The Borjas model is one of negative selection, where those with the lowest ability, and so lowest potential earnings in either Mexico or the US, are most likely to migrate to the US. For example, Borjas (1994, p. 1677) states that

> Relative to natives, immigrants were about 21.7 percent more likely to be high school dropouts in 1970, but are now more than twice as likely to be high school dropouts.

Borjas interprets this apparent decline in immigrant quality as being attributable to changes in the national origin mix of the immigrant flow, as migrant flows have increasingly consisted of individuals from low-income countries, and offers this sort of analysis as evidence of negative selection of migrants to the United States.

It has proven difficult to isolate migrant ability empirically. Borjas has regressed a dummy variable representing the degree of income inequality in the sending country relative to the United States or, closely related, the ratio of earnings of the top households to the earnings of lowest-income households in the sending country, on the level and rate of change of immigrant's earnings (Borjas 1990). He finds that either regressor is inversely associated with earnings. Borjas takes this as reflective of adverse selection of migrants on ability or skill differentials, but the finding that countries with unequal income distributions are likely to send migrants to the United States is at best an inexact test of the Roy model. We will return to an alternative explanation of Borjas' findings later in the paper.

Chiswick (1999) notes that the Roy model is a special case of the human capital model of migration. According to Chiswick, negative selection, if it exists, is a tempering influence on what is likely, according to typical human capital models of migration (*e.g.*, Sjaastad 1962) to be positive selection overall. Chiquiar and Hanson (2005) point out that illegal border crossing entails lower costs for the more educated (who have less difficulty obtaining the needed cash), and that these costs are important in the selection process. In this view, differences in mean earnings between countries swamp the differences in earnings variance that drive the Roy model. High ability individuals, able to bear the financial cost of migration from low-income countries yet still benefiting from higher wages in the United States, are drawn there. Chiquiar and Hanson project as counterfactuals the Mexican earnings of US immigrants, and find them to be solidly in the middle of the Mexican earnings distribution.

The difficulty with such contentions lies in reconciling them with findings like Borjas' on immigrant quality. If migrants actually are those of high earning capacity, relative to their peers at home, what accounts for the finding that, at least for some immigrant groups, immigrant earnings are lower and grow more slowly compared to natives? Schoeni (1997) brings this finding vividly home, showing that Mexican and Central American emigrants have low initial earnings and low rates of growth of earnings compared to US natives, and low rates of growth compared to those who came to the US from other countries. Schoeni controls for migrant education, and notes that Mexicans educated in the United States had nearly twice the schooling of those educated in Mexico, and a much smaller earnings differential compared to the native born. Card (2005) also points out that earnings of foreign-born workers are much lower than those of the native-born, and, attributing this to poor training and language skills of immigrants, sees little prospect of the gap closing. However, using the 1995-2002 Current Population Survey, Card shows that the children of immigrants obtain more education and earn higher wages than comparable third-and-higher generation native born. Taken together, the findings of Schoeni and Card are consistent with the view that some migrants possess innate abilities, attitudes, or other potentially heritable qualities at least equal to non-migrants from their countries of origin. Their own training is sufficiently poor relative to the native-born to sustain a substantial earnings gap, but their children perform well.

Stark and Taylor have argued in a series of papers for the importance of household-level rather than individual-level decision making in migration. In this context, they develop a model of relative household deprivation, and test it on a small sample of Mexican households in two rural villages (Stark and Taylor 1991). They estimate a multinomial logit model of the log odds of migrating domestically or internationally, versus not migrating at all. While they base their discussion on raw coefficients and do not present marginal effects, these are straightforward to calculate.

From their results, we calculate a marginal effect of income on the probability of international migration of 0.41, and a marginal effect of relative income deprivation, a measure that apparently is measured in the same units as income, of 0.09. Thus, they predict that the effect on emigration from poor, rural areas of income-increasing policy changes will differ from the overall effect. Our calculated marginal effect of a year of educational attainment on the probability of US migration, based on the Stark and Taylor multinomial logit coefficients, is -0.02.

We are unable to attach statistical significance levels to any of the Stark and Taylor marginal effects, but they are suggestive of two things. First, relative economic standing matters. It appears that in this case, for all but the most inegalitarian policies, effects on US migration driven by relative income standing are likely to be dominated by absolute income levels but that nevertheless, the marginal effect of relative deprivation is roughly 22% as large as the marginal effect of absolute income levels. Secondly, it appears from the Stark and Taylor results that the less educated, measured in absolute rather than relative terms, are more likely to migrate from rural Mexico to the US. It would have been appealing in the present context had Stark and Taylor examined the impact of relative education, as a proxy for relative deprivation based on future earnings. Unfortunately, given the highly geographically concentrated sample they employ, there is little supply-side variability in education Stark and Taylor could have exploited in these data, and so little that could have been said in any case about relative education and migration.

A model of Mexican-US migration

There are three characteristics that drive our model, none controversial:

1. Migrants choose to migrate where the wage differential, net of migration costs, is positive.
2. Human capital accretions increase wages in both sending and receiving labor markets, though at varying rates.
3. Human capital levels depend on an initial endowment and on subsequent accumulation, and such accumulation is costly.

We assume that the wage received by an individual in Mexico, w_0, is a function of the base Mexican wage μ_0, human capital accumulation h, and the return to human capital in Mexico, $\delta_0(h)$, where $\delta_0'>0$.[5] Human capital accumulation is a function of ability a and skill accumulation s, with skills contributing to human capital accumulation at constant rate π_0 in Mexico. Skills are less costly for those with high ability or for those living in areas with lower cost of education (τ) to obtain, implying $\partial s/\partial a > 0$ and $\partial s/\partial \tau < 0$. Thus:

(1) $$w_0 = \mu_0 + \delta_0(h)$$

(2) $$h = a + \pi_0 s$$

(3) $$s = s(\tau, a)$$

The within-Mexico skill premium per unit of skill accumulated is $\delta'_0\pi_0$. The wage impact of a unit change in education cost, τ, for a Mexican worker in Mexico is

(4) $$\frac{\partial w_0}{\partial \tau} = \delta_0' \pi_0 \frac{\partial s}{\partial \tau}$$

and comparably, for a unit change in ability, the Mexican wage impact is

(5) $$\frac{\partial w_0}{\partial a} = \delta_0' \pi_0 \frac{\partial s}{\partial a}.$$

[5] We suppress an individual-specific subscript throughout for the sake of simplicity.

Let w_1 and similarly subscripted variables represent equivalent quantities in the United States. After Roy (1951), Sjaastad (1962), Borjas (1999) and Chiquiar and Hanson (2005), the decision to migrate is straightforward, based on a comparison of migration costs C with expected wage benefits from migration. The individual chooses to migrate if

(6) $$w_1 - w_0 > C \quad .$$

The distinguishing feature of our model is the explicit consideration of access to education, τ. Consider the impact of a change in Mexican schooling costs or ability, and subsequent within-Mexico generation of human capital, on US earnings for migrants:

(7) $$\frac{\partial w_1}{\partial \tau} = \delta_1' \pi_0 \frac{\partial s}{\partial \tau} \qquad \text{and}$$

(8) $$\frac{\partial w_1}{\partial a} = \delta_1' \pi_0 \frac{\partial s}{\partial a} \quad .$$

Here, the US wages of migrants follow the same general pattern as they would have in Mexico, increasing in ability and decreasing in education costs, but wage levels differ according to differences in returns to human capital ($\delta_j(h)$) in each setting. Defining the net benefit to migration to be $B = w_1 - w_0 - C$ and assuming constant migration costs C, we have the following expression for variation in net benefits to migration:

(9) $$\partial B = (\delta_1' - \delta_0')\pi_0 \left[\frac{\partial s}{\partial a} \partial a + \frac{\partial s}{\partial \tau} \partial \tau \right].$$

B is monotonically related to the probability of migration, and the term ($\delta_1' - \delta_0'$) is the difference in marginal returns to human capital in the US and Mexico. Where this difference is positive, (9) shows that the probability that an individual migrates from Mexico to the US increases with ability but, because the partial derivative of skill accumulation with respect to education costs is negative, the probability of migration decreases with increases in the cost of education.

The stylized Borjas result is that low earners in Mexico, presumably those of low ability, are more likely to come to the United States than are high earners. There are two ways this could happen within the structure of the model. One, the Roy-Borjas negative-selection result, is that the sign of $(\delta'_1 - \delta'_0)$ becomes negative for high earners, so that migration flows consist largely of low earners. It seems unlikely, in large part because of the sizable difference in mean earnings in the US and Mexico, that the Mexican premium to human capital exceeds the US premium for most of the Mexican population. This notion is reinforced by the findings of Chiquiar and Hanson (2005), who show a wage gain even for relatively well-educated Mexican migrants to the US.

Even where $(\delta'_1 - \delta'_0)$ is positive, (9) can yield high rates of migration for low earners. Where human capital accumulation is expensive and returns to human capital are low at the destination, migration probabilities are low, all else constant. At the same time, increasing ability is associated with increasing probabilities of migration, all else constant. The question becomes one of the relative magnitudes of potentially opposing effects. If the ability component dominates the accumulation component of the skill-accumulation function $s(a,\tau)$, as might occur with binding supply constraints in education, and Mexican wages w_0 are low enough compared to US wages,[6] positive net benefits of migration may obtain for those with low levels of human capital accumulation but high levels of ability. While in some ways consistent with Borjas, in that educational constraints make them low earners on arrival in the US, a broader, Roy-inspired

[6] In this respect, the model is somewhat like that of Card's (2001), where individual heterogeneity in the marginal cost of education plays a key role in determining educational attainment.

characterization of these individuals as being of low ability clearly would be inappropriate in this case. Our model also allows for intermediate findings like those of Chiquiar and Hanson, where the two effects yield a mix of migrants—those with some human capital, either through native ability or training, are more likely to come to the US than those without such capital.

An empirical model using Mexican data

The engine of Roy-Sjaastad migration is wage differentials. In Borjas' (1999) interpretation of the model for migration to the US from developing countries, the pull is strongest for unskilled labor, and is posited to be the result of a relatively more diffuse earnings distribution in Mexico. By migrating to the US, even though they remain at the bottom of the US income distribution, they place themselves in the left tail of more compact income distribution. The evidence in favor of this claim is largely circumstantial, consisting of examining educational attainments or labor market outcomes of migrants. In what is to our knowledge the only direct examination of migrants' placement in the sending country earnings distribution, Chiquiar and Hanson (2005) provided strong evidence that, contrary to the prediction of negative self-selection, many Mexicans solidly in the middle of the Mexican earnings distribution migrate to the US. In this case, after Sjaastad, the driving force for migration is the difference in mean wages between the US and Mexico, and the case that migrants are of low quality is weakened.

There are distinctly different roles played by human capital accumulation in various iterations of the Roy-Sjaastad model. Where the focus is on variation in earnings, as in the work of Borjas, increases in Mexican human capital move potential migrants closer to mean Mexican earnings, and so render them less likely to migrate. Where the focus is on the level of earnings, as in Chiquiar and Hanson, or more generally where positive selection of migrants with increasing human capital across the spectrum of earnings is allowed, increases in human capital lead to increases in migration probabilities. The sign and magnitude of the effect of human capital on migration probabilities therefore provides a simple and direct test of the competing hypotheses.

To examine the behavior we posit, we need to differentiate between baseline ability (a) and skill accumulation (s). Fortunately for our purposes, access to education, and so the cost of skill accumulation, varies widely within Mexico. Education through at least high school is easily available in urban areas, but educational access is severely constrained in rural areas, especially in the south. We treat these variations between geographic areas as exogenously determined with regard to international migration, and so interpret geographic differentials in educational attainment as the outcomes of natural experiments, presumably based on variation in education funding. Our empirical strategy is to control for varying costs of human capital attainment by assuming that public resources allocated to education are constant within small geographic areas, so that each individual within an area is subject to the same education funding constraint. We then are able to interpret differences in educational attainment within these small areas as reflective of ability, motivation and other innate differences in human capital, holding cost of educational attainment constant.

The Mexican Migration Project surveyed households in a large number of communities in Mexico[7]. The survey inquired of household members about other, potentially migrant, members and so avoided the problem of interviewing only those who

[7] See Massey *et al*. 1994 for a more complete description of these data.

reside in Mexico at the time of the survey. For all household members, including adult children not currently resident, general demographic information and brief migration measures were collected. Data included age, sex, relationship to head of household, marital status, current economic indicators, and characteristics of the first and last trips made to the US or to other Mexican locations. There also were detailed event histories for each household head, including up to 25 border crossings, and for his or her spouse. The survey was administered during the winter months surrounding the Christmas holidays, in an effort to capture those migrants who live most of the year in the U.S. and returned to Mexico for the holidays. The resulting dataset has information from 71 communities for over 112,000 individuals, roughly one-fifth of whom had US migration experience. Data collection began in 1982, and we use information collected between 1982 and 2006. The unit of analysis is the individual, and each surveyed household can contribute multiple observations. Those individuals who had their first migration experience prior to age 15 were dropped, as they were not likely to have engaged in an independent choice to migrate.[8]

Summary statistics are presented in table 1. The variables are largely self-explanatory, with the possible exceptions of relative education and the wealth variables. The wealth variable is a factor score based on a set of thirteen selected indicators of wealth or financial wellbeing[9]. We take the factor score approach because the thirteen indicators of wealth we employ are likely to be highly correlated with one another. Using factor scores allows us to preserve as much information from these variables as we can,

[8] This restriction is costly, as it eliminates almost half of the sample of US migrants.
[9] The variables are dummies for ownership of land; a stove, refrigerator, washing machine, sewing machine, radio, television, stereo, telephone, or motor vehicle, and whether the respondent's dwelling has running water, electricity, and flush toilets.

and so, we hope, credibly to control for wealth variation in the regressions we run. It is immediately apparent that compared to the full sample, which consists largely of nonmigrants, US migrants are better educated, in both absolute and relative terms; somewhat older, and more likely to be male.

(Table 1 here)

The key variable in our analysis is relative educational attainment, measured as the ratio of individual years attained to the cluster mean of years attained. In poor communities, the mean number of years of school attended was low—the value for the 33rd percentile of educational attainment over the entire sample was 4.29 years—and someone who had more than this level of educational attainment could be construed, in relative terms for that community, to be reasonably well educated. Geographic mobility of children, especially in rural areas, is limited, and so differentials in local education funding levels are likely to be persistent over their youth. Therefore, cross-sectional variation in educational attainment over the entire sample represents the impact of a combination of supply side constraints, shared by all in a locality, and individual variations in aptitude, motivation, and so forth.

We have two concerns regarding the use of this variable as a proxy for ability. First, relative education is calculated based on the community of residence for the respondent at the time of the survey, but its theoretical justification rests on constraints operating during childhood and adolescence. Domestic rural to urban migration is fairly common, and this may lead to some measurement error in relative education. Where this error occurs because of rural-urban migration, the relative education we calculate is based on urban means. Because this results in an understatement of relative education for such internal migrants, we expect that this may bias our results in the direction of conservatism.

Secondly, our analysis rests on the claim that relative education or motivation reflects underlying ability more accurately than does overall years of education attained, because it measures educational attainment in the context of local supply constraints. We will interpret a positive marginal effect of relative education as evidence of positive migrant selection based upon ability, and the converse as evidence of negative selection. The validity of this claim depends on the degree to which relative educational attainment reflects merit over (local) privilege. It probably is the case that relative educational attainment probably is a noisy proxy for ability, so that, after the standard measurement error result, we once again are likely to underestimate the true effect of ability through the use of relative education.[10] While in either case, the estimated effect of relative education is likely to be conservatively estimated, we recognize that there may be less obvious sources of bias that operate to overstate the impact of relative education on migration propensities.

Reflecting the importance of educational attainment as a measure of quality in the literature, we include total years of education attained as a covariate. We include several demographic measures, including age, marital status, and sex. We also include several indicators of resource availability and costs of migration, including family size and three measures of wealth. Three proxies for the availability of migration networks and opportunity costs appear as dummy variables: whether the individual had migrated

[10] The problem may be more severe than simple noise. For example, a more systematic effect may occur if the locally privileged have both easier access to education and reduced likelihood of leaving a comfortable situation. In this case, we are probably again underestimating the true impact of relative education, biasing our result by including those who have high levels of relative education but with (potentially) low levels of ability and low probabilities of leaving home.

domestically, and whether they had immediate family or extended family in the United States.

We estimate several models, regressed on a common set of covariates. All incorporate community-level variation. The first model is a linear regression model on months spent in the United States, with a sample including both migrants and non-migrants. Never-migrants have a value of zero for the dependent variable, and the sum of all months spent in the US is recorded for migrants. The information contained in the dependent variable for this regression therefore is a mixture of migration propensities and durations of stay. We estimate this and subsequent models for a full sample, and separately for subsamples of male and female respondents.

We next attempt to decompose variation in the dependent variable of this simple model into its constituent parts. First, we estimate the determinants of migration probability. A respondent is designated as a migrant if they have reported one or more total months of US migration experience.[11] An important determinant of how long a migrant stays is his or her success in the US labor market, and so we next estimate linear models of the probability that a migrant found employment in the US on their last or current migration. The independent variable here is created from a categorical variable that classifies occupations held by migrants on their last trip to the US. Overall, approximately seventy-seven percent of all migrants were employed during their last migration to the US[12]. Only the migrant subsample is used to estimate this equation. We

[11] Within our sample, there are fifty-three individuals that report at least one migration to the US but who also report having less than one month of US migration experience. They are not counted as migrants in our analysis.
[12] Some of these migrants may still be in the US at the time of the interview.

estimate both of these models as linear probability models with community-level fixed effects.

(Table 2 here)

Table 2 shows that both education variables have distinct impacts on the linear regression for total months in the US. The coefficient of relative education is positive and significant in all cases. For the full sample, its value of 4.75 implies that the mean months spent living in the US for this group, 14.3 months, would increase to 17.7 months with a one standard deviation (0.72) increase in relative education. Absolute education decreases average durations in the US. For the full sample, we estimate that a one standard deviation increase in educational attainment (4.4 years) would decrease duration in the US by 2.1 months. The effect of education, either relative or absolute, is more than twice as large for men as women, and the coefficient of "Male" shows that men, on average, stayed nearly six months longer in the US than did women on their last migration to the US.

The control variables in these results have coefficients much as expected. Younger people are either more likely to go to the US or likely to stay longer than older people, all else constant. We confirm the contention of Chiquiar and Hanson (2005) that those from wealthier households are more likely to come or to stay in the US. We estimate that an individual from a household one standard deviation above mean wealth spent 1.9 more months in the US, all else constant, than someone from a household with average wealth. Married individuals, especially men, are more likely to spend time in the US. Those who have migrated previously within Mexico are less likely to have spent time in the US, and those with migration networks in place are more likely to have spent time in the US than those without such networks. We predict that individuals from communities with mean educational levels one standard deviation below the mean would spend roughly 1.5 more months in the US than those from communities at average educational levels. This is consistent with the notion that migrants are coming from areas of Mexico with comparatively little infrastructure.

The unanswered question from these results is whether variations in duration in the US are due to changes in the probability that an individual migrates to the US in the first place, or to changes in duration or in the probability that he or she stays in the US. As the first step in decomposing the gross "US months" effect, we estimate a model of the probability of ever having migrated to the US, and present the results in Table 3. The determinants of migration are similar to those for total months in the US. Strikingly, those relatively better educated are more likely to have migrated to the US at least once, but those absolutely better educated are less likely to have done so. For males the effect is particularly striking. We estimate that all else constant, being one standard deviation above mean relative education increases the probability of migrating by just over 7 points, a sizable effect compared to the mean probability of ever migrating for males of 25%. Age is not an important determinant of US migration, but those from wealthier households and with access to migration networks display higher probability of ever migrating.

It is instructive to compare the magnitudes of the education effects in two stylized settings. In the first, comparable to rural southern Mexico, adults average four years of education completed. In the second, as might be the case in an urban area like Mexico City, adults average ten years of completed education. Consider someone with eight completed years of education. If they lived in the rural area, they would have relative education of 2.0; in the urban, relative education of 0.8. An otherwise average male with eight years of education has a predicted probability of ever migrating to the US from the stylized rural area of 0.37, and from the stylized urban area of 0.21. We therefore confirm that those with less overall education therefore are more likely to migrate to the US, as predicted by Borjas. However, the subtler underlying finding is that it appears to be those with relatively high levels of education from educationally supply-constrained areas who account for much of this migration.

(Table 3 here)

Given that migrants come to the US, the key question regarding how long they stay is how they fare in the labor market. For the subsample of migrants to the US, we estimated models of the probability of obtaining US employment. Focusing on the results for males for the moment, Tables 4a-4c offer mixed results. In table 4a, which presents marginal effects from a probit equation employing the full sample of migrants and nonmigrants, our finding mirror those for the migration decision. Those with relatively high education for the sending area do better in the US job market. Of all male migrants to the US in our sample, 87% reported finding a job in the US. A one standard deviation increase in relative education increases this by 7 points, an increase of 8%. This effect would be offset by an increase of about 11 years in absolute education. Considering again the stylized male migrants, each with 8 years of education but otherwise at sample averages, we estimate the probability that the migrant from the education-constrained area works at a job in the US to be 0.97, and from the area with higher levels of education, 0.86. Finally, Table 4a shows small but systematic determinants of female employment. The signs and levels of statistical significance are comparable to the other samples, but the magnitudes are much smaller.

(Table 4a – 4c here)

However, much of the variation in the full sample is due to the decision to migrate. The results in Table 4b show a much weaker relationship. While the male sample shows the same qualitative results as Table 4a, magnitudes are substantially reduced. There appears to be little systematic behavior.

It is important to condition for the nonrandom sample selection process inherent in estimating a model of US employment, since only migrants can obtain US employment. We estimate Heckman models in which a probit US employment equation is estimated jointly with a probit migration equation, and present the results in Table 4c. We do not explain variation in US employment well with this model. A likely contributor to this problem is the very high probability of finding employment displayed by most migrants, leading to little variation in outcomes.

If educational constraints operating at the community level are important sources of community level variation, their omission from the models we have examined should be statistically costly. Our approach will be to compare our key coefficients across three forms for each of the three models (US Experience and the probabilities of migrating and of finding subsequent employment). The first form, "Model 1" below, is a simple OLS (or probit, as appropriate), which allows for clustering in the residual at the community level but does not otherwise account for community-level effects. The second, Model 2, is a fixed-effects form, which we implemented by adding community-level dummy variables, and Model 3 is one where we add the community-level mean educational attainment instead of the fixed effects. Our strategy then is to test for differences in three key metrics—the coefficients of relative education, education in years, and the ratio of these coefficients. The fixed effects estimator is well known to be consistent, so differences in our key results from this estimator will be taken as evidence of omitted community-level variation.

(Table 5 here)

Table 5 presents a set of *p*-values based on χ^2 statistics not presented in order to save space for various regression models. The columns of Table 5 list the three subsamples we have employed. There is one vertical panel for each of the three dependent variables used in Tables 2-4. Within each panel, there are subheadings for pairwise comparisons between models, and under each pairing, three statistics. These represents tests that the coefficients of relative education, of education in years, and of the ratio of these two coefficients vary across the models under comparison. So, for example, the top three values in column (1) show *p*-values of .000 for the null hypothesis that the coefficient of relative education is the same in the basic and fixed effects models; that the coefficient of years of education is the same across these two models, and that the ratio of these two coefficients does not differ.

For US Experience, the general result is that community-level effects matter, as the contention that the coefficients we examine do not differ between either the fixed effects model (Model 2) or the mean educational attainment model (Model 3) and the naïve model is almost always rejected. On the other hand, the contention that results from Models 2 and 3 do not differ typically is not rejected. The exception is for the male sample. For the probability of migrating to the US, the results are even more clear-cut.

We have no statistical basis in these data to discriminate between a fixed-effects model and one that controls for community-level variation in educational attainment. This is strong evidence for the impact of relative education in the migration decision. Unfortunately, the imprecision with which the US employment equations are estimated makes it difficult to discriminate between competing models of this outcome.

Discussion

We have developed a model of migration driven by human capital accumulation where, in typical fashion, human capital consists of an endowment of ability augmented through the accumulation of skills. Though very simple, it is sufficient to generate two cases of interest. In the first, which is essentially the Borjas (1999) interpretation of Roy (1951), US earnings premiums drive those at the low end of the Mexican earnings scale to migrate to the US. To be a credible explanation of migration concentrated amongst low-skill immigrants, it must be the case that US wage premiums are relatively higher for less educated than for more educated immigrants. Evidence on whether this is the case is mixed at best, and Chiquiar and Hanson (2005) present the convincing counterpoint that mean earnings are sufficiently high in the US that many across the Mexican income spectrum have an incentive to migrate. In the second case, to the extent that Mexican migrants possess low human capital, the explanation within our model is that they are high-ability individuals who have been constrained in obtaining education.

Our findings are in many ways consistent with Borjas'. Borjas finds that immigrants have low absolute levels of education, and we confirm that, at least when compared to native US workers[13]. Borjas finds that migrants are more likely to come

[13] However, like Chiquiar and Hanson (2005), we find that on average, migrants to the US have more education than nonmigrants.

from countries with higher degrees of income inequality, and we indirectly extend this to the subnational level, as those from areas with lower average levels of education are more likely to migrate to the US than are individuals from areas where education level are higher. Our differences with models reporting negative self-selection of migrants to the US emerge as we look more closely at measures of immigrant quality.

Most notably, Mexicans with high relative levels of education are more likely than those with little education, relatively, to migrate to the United States and to find employment when they arrive. While those with more total years of education are less likely to migrate to the United States, this effect is swamped by the relative education effect. Therefore, we attribute a significant share of the low levels of education Mexican migrants to the United States display to supply constraints operating in their origin localities.

To the extent that relative education captures traits like ability or motivation, a case can be made that the more motivated or innately able are migrating to the US, and so that Mexican migrants are selecting positively on ability. To the extent that this ability is heritable, the findings of Schoeni (1997) and Card (2005) on the labor market advantages enjoyed by migrants' children are consistent with the notion that the migrants themselves are of high innate ability. The Borjas result that those from sending countries where income is more unequally distributed are more likely to come to the US also is consistent with our result, as those typically are the countries of origin from which immigrants of high ability, faced with constraints in obtaining education at home, have the most to gain by immigrating to the US.

We stress, however, that the causal mechanism we propose clearly differs from than that offered by Borjas. The policy implications of our findings are very different from those that emerge from analyses where migrant quality is approximated by years of education or, by extension, labor market outcomes of immigrants. In the absence of supply constraints, years of completed education may well be a reasonable proxy to assess both human capital stocks and ability levels of immigrants. On the other hand, if, as appears to be the case in much of Mexico, educational attainment is supply constrained, completed years of education is flawed as a measure both of the entry-level stock of human capital and the possible trajectory of human capital over time, because the low levels of education we observe causes us to undervalue the ability component of human capital.

It seems from our results that educational supply constraints operate in Mexico, and that (relatively) able but (absolutely) poorly educated immigrants are self-selecting from poorer regions of Mexico. It is likely that Mexico represents the rule rather than an exception amongst developing countries in this regard. If so, observed United States labor market differentials may actually reflect educational supply constraints in sending countries that have the effect of masking relatively high underlying ability of immigrants. Models of negative selection are often used to justify reducing the number of immigrants of particular origin. Rather than tightly restricting immigration, a case can be made from the present results and those of and Chiquiar and Hanson (2005) for an immigration policy that includes a significant training component, potentially easing the transition into the United States economy for relatively able but untrained migrants.

References

Borjas, George J. 1990. *Friends or Strangers: The Impact of Immigrants on the US Economy.* New York: Basic Books.

Borjas, George J. 1991. *Ethnic Capital and Intergenerational Mobility.* **Quarterly Journal of Economics** 107,1 (February): 123-150.

Borjas, George J. 1994. *The Economics of Immigration.* Journal of Economic Literature 32 (4): 1667-1717.

Borjas, George J. 1999. **Heaven's Door: Immigration Policy and the American Economy**. Princeton: Princeton University Press.

Card, David. 2001. *Estimating the Returns to Schooling: Progress on some Persistent Economic Problems*. **Econometrica** 69, no. 5 (Sept.): 1127-1160.

Card, David. 2005. *Is the New Immigration Really So Bad?* **The Economic Journal** 115, no. 507: F300-F323

Chiquiar, David and Gordon Hanson. 2005. *International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States.* **Journal of Political Economy** 113: 239–281.

Chiswick, Barry R. 1999. *Are Immigrants Favorably Self-Selected? An Economic Analysis.* **American Economic Review** 89, no. 2 (May):181-185.

Duleep, Harriet Orcutt and Mark C. Regets. 1999. Immigrants and Human Capital Investment. **American Economic Review** 89, no. 2 (May): 186-191.

Massey, Douglas S., Joaquin Arango, Ali Koucouci, Adela Pelligrino, and J. Edward Taylor. 1994. *An Evaluation of International Migration Theory: The North American Case.* **Population and Development Review** 20: 699-752.

Roy, Andrew D. 1951. “Some Thoughts on the Distribution of Earnings,” **Oxford Economic Papers** 3: 135-146.

Schoeni, Robert F. 1997. *New Evidence on the Economic Progress of Foreign-Born Men in the 1970s and 1980s*. **The Journal of Human Resources** 32, no. 4. (Autumn): 683-740.

Sjaastad, Larry A. 1962. “The costs and returns of human migration”, **Journal of Political Economy** 70 (Supplement): 80-93.

Stark, Oded and J. Edward Taylor. *Migration Incentives, Migration Types: The Role of Relative Deprivation*. **Economic Journal** 101, no. 408 (September): 1163-1178.

Table 1. Descriptive Statistics

Variable	*Description*	*Full Sample*	*Migrants Only*
US Experience, months	Total months individual spent living in the US	6.27 (26.23)	56.67 (57.88)
US Migration	Equals 1 if individual ever migrated to US	0.11 (0.31)	1.00 (0.00)
US Employment	Equals 1 if individual ever worked within the US	0.09 (0.28)	0.77 (0.42)
Relative Education	Individual's educational attainment divided by mean educational attainment of sample cluster	1.00 (0.72)	1.29 (0.62)
Years of Education	Completed years of education	5.97 (4.41)	7.31 (3.53)
Age	In years	27.61 (17.46)	31.32 (10.00)
Household Wealth	Factor score for household amenity and asset ownership	-0.03 (0.84)	0.13 (0.78)
Married	Equals 1 if currently married	0.50 (0.50)	0.71 (0 .45)
Male	Equals 1 if yes	0.49 (0.50)	0.71 (0.45)
Number of Household Members	Includes primary respondent	5.54 (2.80)	4.94 (2.68)
Previous Domestic Migrant	Equals one if indvidual has within-Mexico migration experience	0.18 (0.38)	0.21 (0.41)
Family Network	Equals 1 if any immediate family has past US migration	0.69 (0.46)	0.88 (0.32)
Extended Network	Equals 1 if any extended family has past US migration	0.69 (0.46)	0.83 (0.38)
Eighties	Equals 1 if data collected in the 1980s	0.15 (0.36)	0.09 (0.29)
Nineties	Equals 1 if data collected in the 1990s	0.54 (0.50)	0.61 (0.49)
Mean Cluster Education	Sample cluster mean years of education attained	5.96 (1.41)	5.72 (1.27)
Number of observations		112,220	12,448

Notes: Based on authors' calculations from Mexican Migration Project data, 1982-2006. Standard deviations appear in parentheses below unweighted means.

Table 2. US experience in months

	(1) Full Sample	(2) Males	(3) Females
Relative Education	4.750	6.628	2.678
	(0.000)**	(0.000)**	(0.003)**
Education, Years	-0.498	-0.755	-0.236
	(0.004)**	(0.001)**	(0.102)
Age	0.015	0.028	-0.007
	(0.063)	(0.072)	(0.259)
Household Wealth	2.229	3.045	1.530
	(0.000)**	(0.000)**	(0.000)**
Married	6.051	8.723	4.118
	(0.000)**	(0.000)**	(0.000)**
Male	5.964		
	(0.000)**		
Number of HH members	-0.413	-0.498	-0.340
	(0.000)**	(0.000)**	(0.000)**
Previous domestic migrant	-2.947	-4.593	-1.696
	(0.000)**	(0.000)**	(0.000)**
Family Network	3.530	5.087	2.139
	(0.000)**	(0.000)**	(0.000)**
Extended Network	2.720	4.170	1.474
	(0.000)**	(0.000)**	(0.000)**
Eighties	-5.973	-8.971	-3.036
	(0.000)**	(0.000)**	(0.000)**
Nineties	-1.084	-1.976	-0.070
	(0.194)	(0.103)	(0.906)
Mean Cluster Education	-1.101	-1.879	-0.462
	(0.000)**	(0.000)**	(0.013)*
Constant	4.857	13.205	3.404
	(0.010)*	(0.000)**	(0.019)*
Observations	112220	53043	59177
Number of communities	114	114	114

Notes: Reports coefficients from linear models with community-level clustering in residuals. *p* values in parentheses for two-tailed alternative hypotheses. Values of "0.000" indicate quantities less than 0.001. Asterisks denote statistical significance versus two-tailed alternatives at 5% (*) and 1% (**) levels.

Table 3: Probability of US Migration

	(1) ***Full Sample***	*(2)* ***Males***	*(3)* ***Females***
Relative Education	0.063	0.100	0.036
	(0.000)**	(0.000)**	(0.000)**
Education, Years	-0.005	-0.008	-0.003
	(0.000)**	(0.001)**	(0.010)*
Age	0.000	0.000	0.000
	(0.018)*	(0.008)**	(0.623)
Household Wealth	0.016	0.019	0.015
	(0.000)**	(0.000)**	(0.000)**
Married	0.073	0.117	0.043
	(0.000)**	(0.000)**	(0.000)**
Male	0.099		
	(0.000)**		
Number of HH members	-0.002	-0.000	-0.003
	(0.004)**	(0.817)	(0.000)**
Previous domestic migrant	-0.017	-0.029	-0.009
	(0.000)**	(0.000)**	(0.004)**
Family Network	0.064	0.103	0.038
	(0.000)**	(0.000)**	(0.000)**
Extended Network	0.044	0.075	0.023
	(0.000)**	(0.000)**	(0.000)**
Eighties	-0.044	-0.080	-0.020
	(0.000)**	(0.000)**	(0.008)**
Nineties	0.005	-0.008	0.014
	(0.428)	(0.464)	(0.004)**
Mean Cluster Education	-0.015	-0.030	-0.005
	(0.000)**	(0.000)**	(0.015)*
Observations	112220	53043	59177
Number of communities	114	114	114

Notes: Reports marginal effects at sample means from probit models with community-level clustering in residuals. *p* values in parentheses for two-tailed alternative hypotheses. Values of "0.000" indicate quantities less than 0.001. Asterisks denote statistical significance versus two-tailed alternatives at 5% (*) and 1% (**) levels.

Table 4a: Probability of Finding US Employment (all obs)

	(1) *Full Sample*	*(2)* *Males*	*(3)* *Females*
Relative Education	0.043	0.093	0.018
	(0.000)**	(0.000)**	(0.000)**
Education, Years	-0.003	-0.008	-0.001
	(0.000)**	(0.000)**	(0.052)
Age	0.000	0.000	0.000
	(0.007)**	(0.225)	(0.044)*
Household Wealth	0.010	0.020	0.005
	(0.000)**	(0.000)**	(0.000)**
Married	0.045	0.111	0.012
	(0.000)**	(0.000)**	(0.000)**
Male	0.104		
	(0.000)**		
Number of HH members	-0.000	0.000	-0.001
	(0.469)	(0.632)	(0.017)*
Previous domestic migrant	-0.006	-0.021	0.001
	(0.017)*	(0.000)**	(0.619)
Family Network	0.044	0.093	0.019
	(0.000)**	(0.000)**	(0.000)**
Extended Network	0.033	0.072	0.012
	(0.000)**	(0.000)**	(0.000)**
Eighties	-0.032	-0.073	-0.010
	(0.000)**	(0.000)**	(0.021)*
Nineties	-0.002	-0.013	0.005
	(0.663)	(0.213)	(0.130)
Mean Cluster Education	-0.010	-0.025	-0.001
	(0.000)**	(0.000)**	(0.307)
Observations	112447	53209	59238

Notes: Reports marginal effects at sample means from probit models with community-level clustering in residuals. p values in parentheses for two-tailed alternative hypotheses. Values of "0.000" indicate quantities less than 0.001. Asterisks denote statistical significance versus two-tailed alternatives at 5% (*) and 1% (**) levels.

Table 4b: Probability of Finding US Employment (migrants only)

	(1) *Full Sample*	(2) *Males*	(3) *Females*
Relative Education	0.052	0.056	0.011
	(0.084)	(0.028)*	(0.866)
Education, Years	-0.010	-0.012	0.002
	(0.080)	(0.010)*	(0.855)
Age	-0.002	-0.002	-0.002
	(0.033)*	(0.000)**	(0.245)
Household Wealth	0.012	0.023	-0.026
	(0.089)	(0.000)**	(0.037)*
Married	-0.012	0.049	-0.182
	(0.244)	(0.000)**	(0.000)**
Male	0.415		
	(0.000)**		
Number of HH members	0.005	0.003	0.010
	(0.025)*	(0.111)	(0.028)*
Previous domestic migrant	0.057	0.025	0.121
	(0.000)**	(0.008)**	(0.000)**
Family Network	0.030	0.029	0.007
	(0.035)*	(0.006)**	(0.833)
Extended Network	0.063	0.059	0.029
	(0.000)**	(0.000)**	(0.333)
Eighties	-0.059	-0.048	-0.059
	(0.065)	(0.035)*	(0.402)
Nineties	-0.050	-0.034	-0.061
	(0.006)**	(0.007)**	(0.125)
Mean Cluster Education	0.010	0.006	0.012
	(0.283)	(0.343)	(0.600)
Observations	12448	8805	3643

Notes: Reports marginal effects at sample means from probit models with community-level clustering in residuals. p values in parentheses for two-tailed alternative hypotheses. Values of "0.000" indicate quantities less than 0.001. Asterisks denote statistical significance versus two-tailed alternatives at 5% (*) and 1% (**) levels.

Table 4c: Probability of Finding US Employment (migrants only, endogenous selection)

	(1) **Full Sample**	*(2)* **Males**	*(3)* **Females**
Relative Education	0.021	0.003	0.021
	(0.397)	(0.532)	(0.119)
Education, Years	-0.006	-0.002	0.002
	(0.143)	(0.057)	(0.397)
Age	-0.001	-0.000	-0.000
	(0.002)**	(0.000)**	(0.165)
Household Wealth	0.003	0.003	-0.017
	(0.548)	(0.043)*	(0.003)**
Married	0.037	-0.003	-0.071
	(0.000)**	(0.182)	(0.005)**
Male	0.233		
	(0.000)**		
Number of HH members	0.004	0.001	0.004
	(0.002)**	(0.055)	(0.009)**
Previous domestic migrant	0.049	0.008	0.029
	(0.000)**	(0.000)**	(0.029)**
Family Network	-0.006	-0.007	-0.031
	(0.650)	(0.000)**	(0.000)**
Extended Network	0.028	0.001	-0.014
	(0.081)	(0.590)	(0.000)**
Eighties	-0.023	0.002	0.007
	(0.217)	(0.579)	(0.372)
Nineties	-0.040	-0.006	-0.023
	(0.000)**	(0.005)**	(0.015)*
Mean Cluster Education	-0.014	0.004	0.008
	(0.009)**	(0.000)*	(0.054)
Uncensored observations	12448	8805	3643

Notes: Reports marginal effects at sample means from probit models estimated with endogenous selection on migration and community-level clustering in residuals. Of migrants, 85% of males and 46% of females reported US employment. p values in parentheses for two-tailed alternative hypotheses. Values of "0.000" indicate quantities less than 0.001. Asterisks denote statistical significance versus two-tailed alternatives at 5% (*) and 1% (**) levels.

Table 5. Specification tests on cluster-level variation

	(1) Full Sample	*(2) Males*	*(3) Females*
US Experience			
Model 1 vs. Model 2			
Relative Education	.000**	.000**	.002**
Education, Years	.000**	.000**	.002**
Relative Education / Education in Years	.056	.025*	.381
Model 1 vs. Model 3			
Relative Education	.000**	.000**	.010*
Education, Years	.000**	.000**	.010*
Relative Education / Education in Years	.039*	.018*	.290
Model 2 vs. Model 3			
Relative Education	.062	.025*	.143
Education, Years	.053	.006**	.159
Relative Education / Education in Years	.244	.121	.534
Prob (Migrant)			
Model 1 vs. Model 2			
Relative Education	.000**	.000**	.002**
Education, Years	.000**	.000**	.003**
Relative Education / Education in Years	.008**	.003**	.109
Model 1 vs. Model 3			
Relative Education	.000**	.000**	.011*
Education, Years	.000**	.000**	.011*
Relative Education / Education in Years	.006**	.002**	.095
Model 2 vs. Model 3			
Relative Education	.035*	.067	.097
Education, Years	.057	.075	.112
Relative Education / Education in Years	.275	.333	.310
Prob(US Employment)			
Model 1 vs. Model 2			
Relative Education	.183	.458	.338
Education, Years	.164	.466	.304
Relative Education / Education in Years	.903	.529	.629
Model 1 vs. Model 3			
Relative Education	.248	.297	.593
Education, Years	.247	.296	.592
Relative Education / Education in Years	.979	.445	.891
Model 2 vs. Model 3			
Relative Education	.659	.496	.475
Education, Years	.392	.466	.258
Relative Education / Education in Years	.424	.831	.794

Notes: Values in the table body are p-values of χ^2 statistics for tests comparing selected coefficients estimated with three specifications of indicated models. Model (1) has no controls for communities, other than controlling for clustering in the residual. Model (2) adds individual community level dummy variables to Model (1), and Model (3) adds instead a variable measuring average educational attainment calculated for the community based on responses for each cluster. Dependent variables and coefficients (referenced by variable names) are listed in the first column. Regressions include the baseline set of independent variables employed in regressions reported elsewhere, except that the "Male" indicator variable does not appear in regressions based on Males and Females subsets. Values of "0.000" indicate quantities less than 0.001. Asterisks denote statistical significance at 5% (*) and 1% (**) levels.