SELF-SELECTION PATTERNS IN MEXICO-U.S. MIGRATION: THE ROLE OF MIGRATION NETWORKS

David McKenzie and Hillel Rapoport*

Abstract—This paper examines the role of migration networks in determining self-selection patterns of Mexico-U.S. migration. A simple theoretical framework shows the impact of networks on migration incentives at different education levels and how this affects the composition of migrant skills. Empirically, we find positive or education-neutral selection in communities with weak migrant networks but negative self-selection in communities with stronger networks. This is consistent with high migration costs driving positive or intermediate self-selection, as advocated by Chiquiar and Hanson (2005), and with negative self-selection being driven by lower returns to education in the United States than in Mexico, as advocated by Borjas (1987).

I. Introduction

THE skill level of Mexican migrants to the United States is an issue of important policy relevance on both sides of the border. In the United States, an important element of opposition to immigration centers on the extent to which low-skilled Mexicans depress the wages of low-skilled natives. The effects of emigration on Mexico's development will vary according to whether those who leave are less skilled than those who remain, helping to reduce poverty and inequality, or more skilled, heightening already high inequality levels.

A series of papers have produced conflicting results as to whether Mexican migrants are positively or negatively selected in terms of educational skills. Chiquiar and Hanson (2005) find migration rates to be increasing in education up to relatively high education levels, that is, intermediate or positive selection. Cuecuecha (2005) and Mishra (2007) also find positive selection. These findings have been challenged by Ibarraran and Lubotsky (2007) and Fernández-Huertas (forthcoming), who conclude that there is negative selection, with migrants tending to be less educated than nonmigrants. Orrenius and Zavodny (2005) find intermediate selection, with migrants more likely to be in the middle of the skill distribution than at the low or high end, compared to nonmigrants. In contrast, Caponi (forthcoming) finds a U-shaped relationship, with the highest and lowest educated tending to migrate more than the middle educated.[1]

The contribution of this paper is not to provide yet another estimate of the aggregate effect, but rather to show that the pattern of self-selection can vary substantially across communities depending on the extent of their networks, with positive or neutral self-selection occurring in communities with weak migration networks and negative self-selection occurring in communities with stronger migration networks. Different data sets of communities will thus yield different answers as to the average direction of selection. Given the variety of data sets used in the studies cited, it is unsurprising that a consensus has yet to be reached on the matter.

Self-selection is driven primarily by wage differentials net of migration costs (Sjaastad, 1962). Thus, in theory, various self-selection patterns with respect to education and skills may be observed depending on whether the wage-skill profile is steeper at origin or destination and on whether migration costs increase or decrease with skills. Borjas (1987) concentrates on the wage side and famously argues that individuals migrating from countries with high earnings inequality to countries with low earnings inequality will tend to be negatively self-selected. Income inequality is substantially higher in Mexico than in the United States. The Gini index of income in 2000 was 0.41 in the United States and 0.55 in Mexico, while in the same year, the income share of the highest 10% was 43% in Mexico compared to 30% in the United States (World Bank, 2004). All else equal, one would therefore predict negative self-selection among Mexican emigrants.

This prediction assumes that all migration costs are proportional to wages at home and therefore do not determine self-selection patterns. However, in practice, international migration is costly, involving upfront monetary costs, search and information costs, and psychological costs. These costs are unlikely to be constant across education levels but instead likely to be decreasing in skills (Chiquiar & Hanson, 2005; Cuecuecha, 2005). For example, fixed costs of migration represent fewer hours of work and can be met with no or lower borrowing costs by more educated individuals, and education can help in seeking information. As Chiswick (1999) puts it, the more able are also more efficient in migration. If migration costs are large enough and credit constraints sufficiently binding, one should expect to see positive selection in terms of education because individuals with low education find moving to be too costly.

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* McKenzie: World Bank, CReAM, and IZA: Rapoport: Department of Economics, Bar-Ilan University; EQUIPPE, Universités de Lille; CEPREMAP; and CReAM.

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[1] Mexican emigration is exceptional in that for nearly all other countries of the world, positive selection is the rule (Docquier & Marfouk, 2006). Grogger and Hanson (forthcoming) show that this is nevertheless consistent with the Borjas hypothesis, as emigrants from a given country tend to sort themselves across destinations according to returns to skills: destinations with high wage inequality and less progressive tax-transfer systems tend to receive a higher-skilled mix of immigrants.

The pattern of self-selection therefore should depend on how costly migration is from a given community. Migration networks act to lower the costs of migrating as they provide information on border crossing (including on ways to find and deal with smugglers) and housing services, and they help relax credit constraints (Massey, 1988; Orrenius, 1999; Orrenius & Zavodny, 2005; Dolfin & Genicot, 2010). These effects are likely to benefit low-skill migrants the most. In part, this is due to their being more credit constrained, but may also be due to the fact that ethnic enclaves provide services mainly to migrants with low skills in general and low levels of host language fluency in particular (Borjas, 1999; Chiswick & Miller, 2005; Bauer, Epstein, & Gang, 2005).[2] Networks thus tend to be concentrated in low-skill occupations that require less education. As a result, returns to education in the United States can be lower on average for individuals belonging to communities with strong migration networks, possibly inducing a greater degree of negative self-selection in such communities.

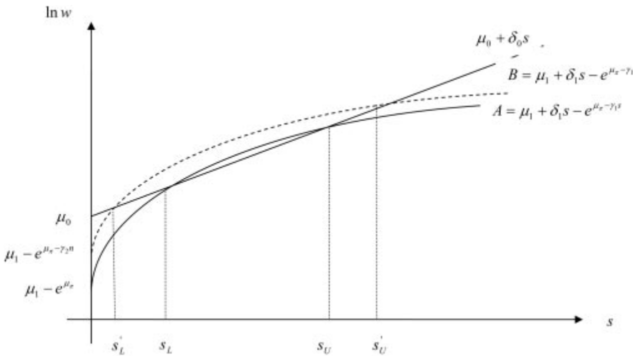
This paper examines the role of migration networks in shaping the self-selection pattern of Mexico-U.S. migration. We begin by augmenting the theoretical model in Chiquiar and Hanson (2005) to allow for network effects and use this to determine the impact of increasing network size on selectivity. Using survey data from Mexico, we then show that negative self-selection on education is more likely in communities with stronger networks. The results are found to be robust to instrumenting community networks with stronger networks, to different definitions of migrants, and to attempts to account for the undercounting of migrants who move with their entire households to the United States. These findings further demonstrate the pivotal role that migration networks play in determining the pattern of migration and go part of the way toward reconciling the conflicting evidence on migrant selectivity arising from the recent literature.

The remainder of the paper is structured as follows. Section II lays out a model of self-selection that includes migration networks. Section III describes our data, section IV provides the main OLS results, section V shows robustness to instrumenting migration networks, and section VI contains additional sensitivity analyses. Section VII concludes.

II. The Model

Starting with Sjaastad (1962), migration has been modeled as an investment decision where prospective migrants make their decision based on the net discounted value of income streams across locations. Given that migration incentives and costs vary according to age, gender, education, and other individual characteristics, immigrants self-select out of the general population nonrandomly. Following Borjas (1987), a series of papers have adapted Roy's (1951) model of self-selection to the issue of Mexican immigration to the United States (Chiquiar & Hanson, 2005; Orrenius & Zavodny, 2005; Ibarraran & Lubotsky, 2007). We extend these models to allow for network effects. Using the notation of Chiquiar and Hanson (2005), the wage equation in Mexico (subscript 0) may be written as (see the solid straight line in figure 1)

FIGURE 1.—MIGRATION NETWORKS AND SELF-SELECTION PATTERNS



$$\ln w_0 = \mu_0 + \delta_0 s, \tag{1}$$

where w is the wage, $\mu > 0$ is the minimal wage level paid in the absence of schooling, $\delta > 0$ is the return to schooling, and s is the level of schooling. Similarly, the wage equation in the United States (subscript 1) may be written as

$$\ln w_1 = \mu_1 + \delta_1 s. \tag{2}$$

Because minimum wages are higher in the United States and relative returns to schooling are higher in Mexico, we assume $\mu_1 > \mu_0$ and $\delta_0 > \delta_1$.[3]

Let C be the migration cost. In line with the migration networks literature (Massey, Goldring & Durand, 1994; Carrington, Detragiache, & Vishwanath, 1996; Bauer et al., 2005; Munshi, 2003; Kanbur & Rapoport, 2005), we assume that it is decreasing with the size of the community migration network, n:

$$C = C(n),\ C' < 0. \tag{3}$$

Expressed in time-equivalent units, the migration cost may be written as

$$\pi = \pi(n, s) = \frac{C(n)}{w_0}. \tag{4}$$

A resident of Mexico will then find it beneficial to migrate to the United States if[4]

[2] Indeed, Bauer et al. (2005) show that enclaves selectively attract people with limited language skills, while all else being equal, migrants with better host-country language proficiency choose destinations with smaller home-country networks.

[3] Chiquiar and Hanson (2005), Ibarraran and Lubotsky (2007), and Cuecuecha (2005) provide evidence supporting these assumptions.

[4] The approximation is valid if π is small, which appears the case if w is defined as the present value of a flow of future incomes.

$$\ln(w_1) - \ln(w_0 + C) \cong \ln(w_1) - \ln(w_0) - \pi > 0. \qquad (5)$$

We assume that time-equivalent migration costs decrease with schooling. This occurs because higher wages require fewer hours of work to pay a fixed fee. It is also consistent with evidence provided by Cuecuecha (2005), who describes a number of other channels leading to this decreasing relationship, including the better ability of more educated individuals to bargain with smugglers. In addition, migration costs, and therefore time-equivalent migration costs, decrease with the size of the community migration network, n:

$$\ln(\pi) = \mu_\pi - \gamma_1 s - \gamma_2 n \qquad (6)$$

so that $\pi = e^{\mu_\pi - \gamma_1 s - \gamma_2 n}$ with $\gamma_1, \gamma_2 > 0$.

Assume first an initial migration network of a given size, which we normalize to 0 without loss of generality. Prospective migrants face a (net of migration cost) wage profile by schooling level at destination, which is given by $A = \mu_1 + \delta_1 s - e^{\mu_\pi - \gamma_1 s}$ (see the solid curved line in figure 1). In order not to rule out the possibility of positive self-selection, we also assume, following Chiquiar and Hanson (2005), that $\mu_1 - \mu_0 < e^{\mu_\pi}$. That is, the intercountry minimum wage differential is not high enough to warrant migration for people with very high migration costs (those with no schooling and no migration network to rely on). For a given size of the migration network, one can then distinguish two schooling thresholds between which people will want to migrate: s_L, below which migration costs are so high that migration is not profitable, and s_U, above which returns to schooling in Mexico are high enough to discourage migration (see figure 1).

The effect of expanding (or introducing) migration networks is to decrease migration costs at all schooling levels. Diagrammatically, this means an upward shift of the wage-schooling profile at destination following the introduction or expansion of migration networks. In addition, schooling and networks are substitutes in lowering the cost of migration. The new wage-schooling profile at destination is now given by $B \equiv \mu_1 + \delta_1 s - e^{\mu_\pi - \gamma_1 s - \gamma_2 n}$ (see the dashed curved line in figure 1), with the two profiles A and B converging at high levels of schooling as the reduction in migration costs is strongest at low schooling levels. This can be stated formally as:

Proposition 1. *Larger migrant networks increase migration incentives (i) at all schooling levels and (ii) more so at low schooling levels.*

PROOF: See the appendix.

Following the expansion of networks, a change in migration incentives (in wages at destination net of migration costs) defines two new threshold values of s, s'_L and s'_U, with $s'_L < s_L$ and $s'_U > s_U$. As migration networks expand, more people are willing to migrate at both ends of the migrants' schooling distribution. How will this translate in terms of self-selection patterns? In all likelihood, larger networks will reinforce, or increase the chances of obtaining, negative self-selection. To show why this is the case, consider the most realistic case where there are and will always be nonmigrants at the two ends of the schooling distribution (that is, the support of s is $[0, \bar{s}]$ and $s'_L > 0$, $s'_U < \bar{s}$). In this configuration, we know that networks will act to increase the number of migrants and that the additional migrants will come from the two intervals $(s_L - s'_L)$ and $(s_U - s'_U)$. The impact in terms of migrants' skills will depend on which of these two intervals is longer and on the density of the schooling distribution on the two intervals. In the following, we focus on the length of the two segments and rule out the possibility that the density of the schooling distribution is higher on $(s_U - s'_U)$ than on $(s_L - s'_L)$, which is quite realistic. Hence, our results hold true for any distribution for which the density is not increasing in schooling.

Proposition 2. *Assuming that the support of s is $[0, \bar{s}]$ and $s'_L > 0$, $s'_U < \bar{s}$,*

(a) *An increase in the migration network increases the range of lower schooling levels that wants to migrate more than it increases the range of higher schooling levels that wants to migrate: $|s_L - s'_L| > |s_U - s'_U|$.*
(b) *Providing that the density of the schooling distribution is not increasing in schooling, larger migration networks reduce average levels of schooling among migrants; all else equal, this increases the likelihood or degree of migrants' negative self-selection.*

PROOF: See the appendix.

III. Data

The main source of data is the 1997 Encuesta Nacional de la Dinámica Demográfica (ENADID; National Survey of Demographic Dynamics) conducted by Instituto Nacional de Estadística, Geografía e Informática (INECI), Mexico's national statistical agency, in the last quarter of 1997.[5] ENADID is a large, nationally representative demographic survey, with approximately 2,000 households surveyed in each state, resulting in a total sample of 73,412 households.

The ENADID survey has been widely used in the study of Mexican migration.[6] Other studies of migrant selection from Mexico have used the U.S. Census, Mexican Census, and data from the Mexican Migration Project (MMP). The

[5] Survey methodology, summary tables, and questionnaires are contained in INEGI (1999).

[6] Google Scholar shows 171 papers using the ENADID with migration. Some examples include Massey and Zenteno (2000), Marcelli and Cornelius (2001), Hildebrandt and McKenzie (2005), and McKenzie and Rapoport (2007, forthcoming).

TABLE 1.—MARITAL STATUS OF RECENT MEXICAN IMMIGRANTS IN THE U.S. CENSUS

	Males	Females
Married, with spouse present	14.4%	48.3%
Married, with spouse absent	26.9	8.7
Separated	1.8	3.7
Divorced	1.5	2.4
Widowed	0.2	0.7
Never married or single	55.2	36.1

Source: US Census 5% public use sample (Ruggles et al., 2004).
Note: Immigrants are those born in Mexico who migrated to the United States in past two years.

U.S. Census suffers from an undercount of illegal migrants, who tend to be of low education (Ibarraran & Lubotsky, 2007). Moreover, it is not suitable for our study since it contains no information on which community in Mexico a migrant came from. The Mexican Census does contain this information, but collects data only on whether an individual has migrated within the past five years. As such, it will classify as a nonmigrant an individual who migrated six years ago, leading us to prefer the ENADID. Nevertheless, we will examine robustness to a definition of migration equal to that used in the Mexican Census. The MMP contains rich life histories of migration, but it is not nationally representative and, in particular, samples only a small number of communities with small migration networks (see McKenzie & Rapoport, 2007). Since most MMP communities have reasonably large networks, this makes it difficult to see how migration varies with network size starting from a low level. The ENADID provides a balance between the depth of migration information in the MMP and the comprehensive coverage of communities with both low and high networks found in the Mexican Census.

A. *Measuring Migration*

The ENADID survey asks whether household members have ever been to the United States in search of work. This information is collected for all individuals who normally live in the household, even if they are temporarily studying or working elsewhere, and includes information on the number of times an individual has been abroad and the date of the last visit. In addition, the survey asks whether there are any individuals who were living in the household five years ago who have moved abroad, regardless of whether they are currently considered part of the household. Using these questions, we classify each individual as ever migrating to the United States, our main variable of interest, and whether they have migrated in the past five years, the census definition, which we will consider for robustness.

As with other Mexico-based surveys of migration, the ENADID captures data only on migrants who have either returned to Mexico or have at least one household member remaining in Mexico. As a result, it will tend to underrepresent permanent migrants (Hanson, 2006) who are likely to take their whole household. In table 1, we use the 5% public use sample of the 2000 U.S. Census (Ruggles et al., 2004) to examine the marital status of Mexican migrants 18 to 45 years old who arrived in the United States within two years of the census. We see that 14.4% of male migrants are married, with their spouse present. These individuals are likely not to be reported on in Mexico-based surveys. However, the majority of migrants are either single or married with a spouse remaining in Mexico, and so should be reported on from Mexico. The problem is much worse with females, with 48% of all recent migrants in the United States being married with spouse present.

The main concern with this undercount for our analysis is that the education levels of migrants who are not reported in the ENADID may differ from the education levels of migrants who are reported. Strong evidence suggests that this is the case. For example, 16.0% of the male migrants in table 1 who have a spouse present in the United States have post–high school education, compared to only 8.3% of those in the other marital categories. Ibarraran and Lubotsky (2007) compare the U.S. and Mexican censuses and also conclude that migrants who are excluded in the Mexican census are likely to be more educated.

Given these concerns, we do not look at self-selection among female migrants; with only half of all female migrants likely to be reported on in the ENADID, we consider the likely bias from doing so to be too severe. In addition, since female migration is so closely tied to the migration of the spouse, the theory above is less directly applicable for females. For males, the ENADID is likely to measure 86% of migrants, and we carry out robustness exercises to see how sensitive our results are to those who are undercounted.

Finally, we restrict our analysis to males aged 15 to 49. Very few individuals migrate before age 15 in our sample, and many are still completing schooling. The upper age limit allows us to concentrate on prime working-age individuals, in common with other studies. Furthermore, it removes concerns about education-selective mortality, which are likely to arise if we consider older samples. Nonetheless, we will show that our main results are robust to considering all males age 15 and above.

B. *Measuring the Community Network*

We follow Massey et al. (1994) in measuring the community migration network by the proportion of all individuals aged 15 and over in a given community who have ever migrated. Since our focus is on male migration, we modify this measure to be the proportion of all males age 15 and over in a community who have ever migrated.[7] We restrict our analysis to municipalities in which at least fifty households were interviewed in the survey in order to measure the community migration network. This results in data on 62,800 males aged 15 to 49 in 304 communities for our analysis. Sample statistics are shown in table 2. Since the

[7] Our results are robust to using the network formed by both male and female migrants. We do not include the individual himself when constructing the network variable.

TABLE 2.—SUMMARY STATISTICS OF KEY VARIABLES

Individual-Level Variables	Number of Observations	All Males 15–49 Mean	s.d.	Migrant Mean	Nonmigrant Mean	T test of difference (p-value)
All communities						
Proportion ever migrated	62,800	0.090		1	0	
Age	62,800	28.9	9.7	33.0	28.5	0.000
Years of education	62,800	8.7	4.4	7.33	8.79	0.000
Proportion married	62,800	0.56		0.80	0.54	0.000
Proportion who are household heads	62,800	0.52		0.76	0.49	0.000
Communities with 100,000 or less population						
Proportion ever migrated	28,602	0.118		1	0	
Age	28,602	28.7	9.8	32.9	28.1	0.000
Years of education	28,602	7.2	4.1	6.29	7.36	0.000
Proportion married	28,602	0.57		0.82	0.54	0.000
Proportion who are household heads	28,602	0.52		0.77	0.48	0.000

Community-Level Variables (communities with 100,000 or less population)	Number of Communities	Mean	s.d.
Community migration prevalence	260	0.118	0.123
State migration rate in 1924	260	0.0068	0.0082
Percent of rural households owning land in 1910	254	2.89	2.17
Male school attendance in 1930 (% of 6 to 10 year olds)	260	45.10	12.00
Gini of schooling years for males 15–20 in 1960	260	0.51	0.10
Average years of schooling of males in 1960	260	2.95	0.84
Gini of household income in 1960	260	0.75	0.10

Source: 15–49 year old males in ENADID (1997).

role of networks is likely to be greater outside large cities, we will also carry out the analysis for individuals living in locations of less than 100,000 population, and less than 20,000 population. This reduces the sample to 22,039 to 28,602 individuals in 260 communities.[8] In the overall sample, 9% of males aged 15 to 49 have ever migrated to the United States, with this increasing to 11.8% in communities with population less than 100,000 and 12.7% in communities with population less than 20,000.

Table 2 also summarizes the main variables of interest separately by migrant status. We see on average that migrants have significantly fewer years of schooling than nonmigrants: the mean years of schooling are 8.8 for nonmigrants compared to 7.3 for migrants. However, migrants are also older, more likely to be married, and more likely to be a household head. We therefore need to control for these differences in estimating the direction of educational self-selection.

IV. OLS Estimates of Educational Self-Selection

The main prediction of the theory is that larger migration networks will reduce the average schooling levels of migrants, making negative self-selection more likely. To test this, we estimate the following equation for the education of male i in community c:

$$\begin{aligned} Education_{i,c} = \alpha &+ \beta Migration_{i,c} + \gamma Network_c \\ &+ \lambda Migration_{i,c} \times Network_c \\ &+ \phi' X_{i,c} + \theta' Z_c + \varepsilon_{i,c}, \end{aligned} \tag{7}$$

where $Migration_{i,c}$ is an indicator variable taking the value 1 if individual i has ever migrated to the United States and 0 otherwise; $Network_c$ is the community migration prevalence among males in community c; and $X_{i,c}$ and Z_c are control variables capturing individual and community characteristics, respectively. The individual characteristics are five-year age group dummies for age, a dummy for being married, and a dummy for being a household head. The community characteristics are controls for community population size and historic variables, which will be discussed further below.

The theory predicts further that within communities, migrants should have less education than nonmigrants the larger is the community network. We therefore also estimate equation (7) with municipality fixed effects. The main coefficient of interest is λ, the coefficient on the interaction between being a migrant and the size of the community network. Negative self-selection will be more likely in communities with strong networks if λ is negative. The other main coefficient of interest is β, which gives the direction of self-selection in communities with no migration network. This will enable us to detect whether positive or neutral self-selection is present in communities with small networks.

Table 3 presents the results of estimating equation (7) via OLS. Column 1 shows the results for Mexico as a whole,

[8] Another reason to focus on smaller communities is a measurement one: there may be networks from city neighborhoods, but the neighborhood is not specified in the survey.

TABLE 3.—OLS RESULTS FOR THE RELATIONSHIP BETWEEN MALE MIGRATION AND EDUCATION
DEPENDENT VARIABLE: YEARS OF EDUCATION ATTAINED FOR MALES AGED 15 TO 49

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ever Migrated	−0.566***	0.126	0.390	−0.560***	0.114	0.331*	−0.781***	−0.125	0.0892
	(0.20)	(0.23)	(0.25)	(0.18)	(0.18)	(0.19)	(0.21)	(0.17)	(0.17)
Community Migration Network	−1.692*	−1.204	−0.578	−1.663**	−1.045	−0.548			
	(0.86)	(0.91)	(1.06)	(0.71)	(0.75)	(0.91)			
Ever Migrated × Community Migration Network	−1.632*	−3.031***	−3.442***	−1.667**	−3.009***	−3.192***	−1.323	−2.008**	−1.576**
	(0.85)	(0.98)	(1.15)	(0.68)	(0.77)	(0.85)	(0.84)	(0.76)	(0.66)
Age 20 to 24	1.008***	0.438***	0.268***	0.993***	0.472***	0.282**	0.981***	0.352***	0.132
	(0.062)	(0.093)	(0.096)	(0.060)	(0.093)	(0.10)	(0.061)	(0.095)	(0.096)
Age 25 to 29	1.397***	0.571***	0.366***	1.350***	0.569***	0.344***	1.371***	0.438***	0.134
	(0.086)	(0.090)	(0.10)	(0.064)	(0.096)	(0.11)	(0.078)	(0.088)	(0.11)
Age 30 to 34	1.356***	0.373***	0.110	1.324***	0.389***	0.0902	1.302***	0.166	−0.236*
	(0.12)	(0.13)	(0.13)	(0.10)	(0.13)	(0.13)	(0.11)	(0.11)	(0.12)
Age 35 to 39	1.072***	−0.208	−0.582***	1.015***	−0.191	−0.583***	0.994***	−0.435***	−0.896***
	(0.14)	(0.17)	(0.16)	(0.12)	(0.16)	(0.16)	(0.13)	(0.15)	(0.15)
Age 40 to 44	0.308**	−1.037***	−1.531***	0.218**	−1.026***	−1.544***	0.231*	−1.223***	−1.834***
	(0.14)	(0.15)	(0.17)	(0.10)	(0.16)	(0.17)	(0.13)	(0.15)	(0.16)
Age 45 to 49	−0.451***	−2.094***	−2.510***	−0.511***	−2.064***	−2.481***	−0.548***	−2.238***	−2.769***
	(0.15)	(0.14)	(0.15)	(0.13)	(0.15)	(0.16)	(0.14)	(0.15)	(0.16)
Married	−0.916***	−0.427***	−0.313***	−0.909***	−0.476***	−0.348***	−0.894***	−0.377***	−0.224**
	(0.067)	(0.096)	(0.11)	(0.057)	(0.087)	(0.10)	(0.063)	(0.097)	(0.11)
Household head	0.300***	−0.0712	−0.276**	0.308***	−0.0686	−0.278**	0.388***	0.0437	−0.174*
	(0.077)	(0.11)	(0.11)	(0.080)	(0.11)	(0.11)	(0.072)	(0.088)	(0.085)
Population 100,000+	3.085***			3.067***					
	(0.15)			(0.13)					
Population 20,000–99,999	2.408***	2.455***		2.389***	2.433***				
	(0.20)	(0.20)		(0.19)	(0.20)				
Population 15,000–19,999	1.674***	1.663***		1.675***	1.598***				
	(0.23)	(0.24)		(0.24)	(0.25)				
Proportion of rural households owning land in 1910				−0.0367	−0.0179	−0.0230			
				(0.033)	(0.047)	(0.058)			
Male school attendance rate in 1930				0.00191	0.0112	0.0237			
				(0.0069)	(0.0086)	(0.014)			
Gini of household income 1960				2.969***	2.645***	3.109***			
				(0.86)	(0.87)	(1.07)			
Gini of male schooling in 1960				−2.807*	−3.788**	−3.293			
				(1.60)	(1.57)	(2.13)			
Average male years of schooling in 1960				−0.0782	−0.182	−0.0904			
				(0.19)	(0.20)	(0.21)			
Constant	6.545***	7.129***	7.424***	6.021***	7.125***	6.028**	8.637***	8.674***	10.87***
	(0.19)	(0.19)	(0.20)	(1.69)	(1.69)	(2.29)	(0.067)	(0.076)	(0.086)
Population	All	<100K	<20K	All	<100K	<20K	All	<100K	<20K
Municipality fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
Observations	62,800	28,602	22,039	58,443	27,211	21,054	62,800	28,602	22,039
R^2	0.15	0.12	0.07	0.15	0.13	0.09	0.16	0.17	0.19

Note: Robust standard errors in parentheses clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

combining urban and rural areas. The coefficient on ever migrated is −0.57 and is statistically significant at the 1% significance level. The interaction with the community migration network is negative, and significant at the 10% level. Thus, for Mexico as a whole, there is negative self-selection of migrants in terms of education in our sample, with this negative self-selection greater in communities with stronger migrant networks, as predicted by the theory. Columns 2 and 3 then restrict to less urban areas, with column 2 showing populations of 100,000 or less and column 3 showing communities of 20,000 or less. As hypothesized, the interaction with the community network is larger in less urban communities, suggesting that networks play a more important role in self-selection outside urban areas. The size of the interaction is economically meaningful as well as statistically significant: a 1 standard deviation change in the size of the community network (0.12) is associated with 0.37 fewer years of education among migrants in the community. The point estimates of β are positive and insignificant in both specifications, suggesting positive or neutral self-selection in communities with weak networks.

These results continue to hold in columns 4 through 6, which add controls for historic conditions that might influence schooling and migration. The point estimates are similar in size, although slightly more precise, leading to the estimate of β of 0.33 being significant at the 10% level in communities with a population below 20,000. That is, there is weak evidence of positive self-selection in more rural communities with small networks. Combining the positive point estimate on migration and negative interaction with community network allows us to easily compute the level of the network at which education self-selection becomes negative. This occurs when 3.8% of males have ever migrated in communities with 100,000 or less and when 10% of males have ever migrated in communities with 20,000 or less. Thirty-six percent of individuals living in communities of 100,000 or less have a community network less than or equal to 3.8%, and 54% of individuals in communities with 20,000 or less have a community network less than or equal to 10%. Thus, there is positive self-selection on education for one-third to one-half of individuals in rural areas.

Columns 7 through 9 then add municipality fixed effects. The interaction term remains negative and is significant in communities with 100,000 or less population and communities with 20,000 or less population. That is, within communities we see more negative self-selection the stronger is the migrant network. The point estimates of β are negative and insignificant for the 100,000 or less population and positive and insignificant for the 20,000 or less population specifications. Thus, we cannot reject neutral (sometimes called intermediate) self-selection on education in rural areas for communities with weak networks. Taking the point estimate in column 9, we would have positive self-selection for the 47% of individuals in communities with less than 20,000 population who have a migrant network less than 5.7% of the population.

V. Instrumental Variables Estimation of the Network Effect and Its Interaction

The OLS results in section IV allow us to describe factually how the degree of self-selection varies with a measure of the strength of the migration network in the community an individual lives in. This fits with the descriptive nature of the existing literature on self-selection and shows that the pattern of self-selection one finds will vary depending on the communities one looks at. However, if we wish to claim that the strength of the community migration network has a causal impact on the degree of educational self-selection, we need to be concerned about the possible endogeneity of the community migration network. In particular, the concern is that the community migration network may be correlated with the educational selectivity of migration. For example, a community with a poor schooling infrastructure may have low levels of education and many people migrating to seek better lives for their children. This would lead us to spuriously find that negative selection on education occurs more in high-migration communities.

To account for this concern, we follow Woodruff and Zenteno (2007) and a number of subsequent studies in using historic state-level migration rates as an instrument for current migration networks.[9] In particular, we use the U.S. migration rate from 1924 for the state in which the migrant household is located, taken from Foerster (1925). Likewise, we will use the interaction between an individual's migration status and historic migration networks as an instrument for the interaction between their migration status and community migration prevalence. The main argument to justify the use of this instrument is that these historic migration rates were the result of the pattern of the arrival of the railroad system in Mexico, coupled with changes in U.S. demand conditions for agricultural labor. As migration networks lower the cost of migration for future migrants, they then become self-perpetuating.[10]

This historic migration rate and its interaction with individual migration status are strong predictors of current community migration prevalence and its interaction. Table A1 in the appendix shows first-stage F-statistics between 24.5 and 41.6. The instrument relevance condition is thus satisfied. To justify the exclusion restriction, we need to argue that these historic rates affect the educational selectivity of migration only through current migration networks. A potential threat to this instrument is that communities that responded more to the expansion of the railroad may have been ones with historically poor schooling infrastructure and inequality, or that the development of the railroads ushered in the expansion of infrastructure such as schooling facilities. This could affect current education through the intergenerational transmission of schooling and the inertia in schooling infrastructure. To allow for this possibility, we control for a number of historic variables that capture schooling access, achievement, and equality, and for historic measures of inequality. Column 1 of table A1 shows that these historic development indicators are not significant predictors of historic migration rates. We will also show that our 2SLS estimates are robust to whether we control for these historic variables.

Table 4 presents the 2SLS estimates of equation (7), with analogous specifications to those used in table 3. We note first that the size and sign of the coefficients in columns 1 to 3 are similar to those in columns 4 to 6, showing that the results do not change very much whether or not we control for historic development indicators. Second, and most important, the main coefficient of interest, λ, the interaction between individual migration and community network, is negative in all specifications and statistically significant in most. This confirms that we are more likely to find negative self-selection in communities with stronger migration networks. The size of the interaction coefficients is larger than in the OLS specifications, although in all cases, the confidence intervals for the 2SLS estimates overlap with those of the OLS estimates. The 2SLS estimates may be larger in magnitude than the OLS estimates because of omitted variables that are positively correlated with the education and the community network of migrants or because instrumenting reduces attenuation bias arising from classical measurement error. Such measurement error can arise due to

[9] Hanson and Woodruff (2003), McKenzie and Rapoport (2007, forthcoming), López-Córdoba (2005), and Hildebrandt and McKenzie (2005) all employ historic migration rates as instruments for current migration.

[10] Hildebrandt and McKenzie (2005) and McKenzie and Rapoport (2007) provide more detailed discussion of the historic processes involved.

TABLE 4.—2SLS RESULTS FOR THE RELATIONSHIP BETWEEN MALE MIGRATION AND EDUCATION
DEPENDENT VARIABLE: YEARS OF EDUCATION ATTAINED FOR MALES AGED 15 TO 49

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ever Migrated	0.146	0.376	0.524	0.418	0.740	0.939	−0.0808	0.146	0.0218
	(0.59)	(0.49)	(0.54)	(0.62)	(0.48)	(0.58)	(0.32)	(0.35)	(0.36)
Community Migration Network	−1.762	−0.113	−0.646	−1.960	−0.690	−1.976			
	(1.96)	(1.57)	(1.75)	(1.43)	(1.01)	(1.30)			
Ever Migrated × Community Migration Network	−5.683	−4.786**	−4.106*	−7.029**	−5.959***	−5.030*	−5.759***	−3.347**	−1.263
	(3.48)	(2.21)	(2.49)	(3.58)	(2.10)	(2.60)	(2.00)	(1.69)	(1.60)
Age 20 to 24	1.011***	0.452***	0.270***	0.996***	0.478***	0.266**	0.990***	0.356***	0.132*
	(0.061)	(0.086)	(0.089)	(0.061)	(0.092)	(0.10)	(0.043)	(0.063)	(0.070)
Age 25 to 29	1.397***	0.588***	0.376***	1.349***	0.574***	0.325***	1.380***	0.441***	0.134
	(0.082)	(0.079)	(0.098)	(0.065)	(0.091)	(0.12)	(0.056)	(0.081)	(0.089)
Age 30 to 34	1.354***	0.388***	0.114	1.320***	0.390***	0.0641	1.311***	0.169*	−0.237**
	(0.12)	(0.12)	(0.13)	(0.10)	(0.13)	(0.13)	(0.065)	(0.091)	(0.099)
Age 35 to 39	1.071***	−0.193	−0.579***	1.011***	−0.189	−0.612***	1.002***	−0.433***	−0.897***
	(0.13)	(0.16)	(0.16)	(0.12)	(0.16)	(0.17)	(0.073)	(0.10)	(0.11)
Age 40 to 44	0.308**	−1.024***	−1.539***	0.215**	−1.023***	−1.578***	0.239***	−1.221***	−1.835***
	(0.13)	(0.14)	(0.16)	(0.10)	(0.16)	(0.17)	(0.079)	(0.11)	(0.11)
Age 45 to 49	−0.452***	−2.084***	−2.518***	−0.512***	−2.060***	−2.510***	−0.542***	−2.236***	−2.770***
	(0.15)	(0.14)	(0.14)	(0.13)	(0.15)	(0.16)	(0.086)	(0.11)	(0.12)
Married	−0.916***	−0.421***	−0.306***	−0.909***	−0.475***	−0.354***	−0.892***	−0.376***	−0.224***
	(0.066)	(0.093)	(0.11)	(0.056)	(0.086)	(0.10)	(0.056)	(0.079)	(0.087)
Household head	0.302***	−0.0681	−0.288***	0.310***	−0.0664	−0.281**	0.389***	0.0443	−0.174**
	(0.076)	(0.11)	(0.11)	(0.080)	(0.11)	(0.11)	(0.056)	(0.078)	(0.086)
Population 100,000+	3.034***			2.991***					
	(0.17)			(0.15)					
Population 20,000–99,999	2.369***	2.450***		2.336***	2.412***				
	(0.20)	(0.20)		(0.18)	(0.20)				
Population 15,000–19,999	1.708***	1.614***	1.641***	1.729***	1.598***	1.619***			
	(0.24)	(0.25)	(0.25)	(0.25)	(0.25)	(0.26)			
Proportion of rural households owning land in 1910				−0.0318	−0.0209	−0.0177			
				(0.033)	(0.044)	(0.057)			
Male school attendance rate in 1930				0.00196	0.0114	0.0174			
				(0.0065)	(0.0080)	(0.012)			
Gini of household income 1960				3.050***	2.627***	3.256***			
				(0.84)	(0.89)	(1.07)			
Gini of male schooling in 1960				−2.782*	−3.957***	−3.341*			
				(1.49)	(1.53)	(1.90)			
Average male years of schooling in 1960				−0.0821	−0.215	−0.0679			
				(0.19)	(0.21)	(0.23)			
Constant	6.581***	7.010***	7.311***	6.016***	7.289***	6.195***	10.17***	6.855***	7.202***
	(0.29)	(0.28)	(0.28)	(1.62)	(1.69)	(2.20)	(0.18)	(0.49)	(0.48)
Population	All	<100K	<20K	All	<100K	<20K	All	<100K	<20K
Municipality fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
First-stage F-statistics									
On community migration network	7.44	10.99	9.40	40.23	41.57	29.04			
On network × migration	10.32	5.25	4.74	14.64	24.51	16.09	519.0	574.3	533.2
Observations	62,800	28,602	22,039	58,443	27,211	21,054	62,800	28,602	22,039

Note: Robust standard errors in parentheses with standard errors clustered at state level. *** $p \leq 0.01$, ** $p < 0.05$, * $p < 0.1$. Instruments used are the 1924 state migration rate and its interaction with individual migration status.

sample sizes as small as fifty households being used to estimate the migration network in a given community.

The third point to note in table 4 is that for communities of population of fewer than 100,000, the point estimates on ever migrated (the coefficient β) are always positive but never statistically significant. That is, we find positive or neutral self-selection on education for individuals in communities with small or weak networks. The level of community network at which negative self-selection occurs is at 12.4% (column 5) or 4.4% (column 8), corresponding to between 41% and 62% of individuals living in communities below 100,000 population for which positive self-selection obtains. The estimates in column 8 are more robust, since they include municipal fixed effects, and show that within communities with strong networks, negative self-selection occurs, whereas within communities with weak networks (those where less than 4.4% of males have ever migrated), positive self-selection occurs. This accords with the historic evidence in Feliciano (2001), who found that migrants in 1910 (a time when migrant networks were first forming) had higher literacy rates than nonmigrants and thus were positively self-selected within communities.

Thus, we find that in communities with weak migration networks, migrants tend to be selected from the upper-middle of the education distribution, which concurs with Chiquiar and Hanson's (2005) description of selectivity.

TABLE 5.—ROBUSTNESS
DEPENDENT VARIABLE: YEARS OF SCHOOLING ATTAINED

	Table 3 or 4 Specification (1)	Top Coding Education at Sixteen Years (2)	Top Coding Education at Twelve Years (3)	Census Definition of Migrant (4)	All Males 15 and Older (5)	Reweighting for Undercount of Movers (6)
A. OLS Results with State-Level Controls (Compare Table 3, Column 5)						
Ever migrated	0.114	0.144	0.277*	−0.256	0.0199	0.116
	(0.18)	(0.18)	(0.15)	(0.23)	(0.21)	(0.18)
Community migration network	−1.045	−1.084	−1.192*	−1.363*	−0.881	−1.044
	(0.75)	(0.74)	(0.67)	(0.74)	(0.64)	(0.75)
Ever Migrated × Community Migration Network	−3.009***	−2.935***	−2.547***	−2.253**	−2.005**	−3.000***
	(0.77)	(0.75)	(0.67)	(0.94)	(0.92)	(0.76)
B. OLS Results with Municipality Fixed Effects (Compare Table 3, Column 8)						
Ever migrated	−0.182	−0.145	−0.0125	−0.508**	−0.264	−0.178
	(0.22)	(0.21)	(0.16)	(0.21)	(0.23)	(0.22)
Community migration network	−9.888	−10.71	−1.308	16.14	−20.34	−8.362
	(17.0)	(16.3)	(13.9)	(12.0)	(19.8)	(16.6)
Ever Migrated × Community Migration Network	−2.127***	−2.110***	−1.772***	−0.614	−1.440*	−2.070***
	(0.71)	(0.70)	(0.60)	(0.86)	(0.77)	(0.71)
C. 2SLS Results with State-Level Controls (Compare Table 4, Column 5)						
Ever migrated	0.740	0.769	0.887*	0.610	0.407	0.754
	(0.48)	(0.47)	(0.46)	(0.50)	(0.37)	(0.49)
Community migration network	−0.690	−0.730	−1.101	−1.095	−0.611	−0.679
	(1.01)	(1.00)	(0.98)	(0.92)	(0.80)	(1.01)
Ever Migrated × Community Migration Network	−5.959***	−5.883***	−5.287**	−5.979***	−3.735**	−6.013***
	(2.10)	(2.07)	(2.07)	(1.99)	(1.56)	(2.14)
D. 2SLS Results with Municipality Fixed Effects (Compare Table 4, Column 8)						
Ever Migrated	0.146	0.206	0.337	0.0848	0.0593	0.155
	(0.35)	(0.34)	(0.30)	(0.40)	(0.26)	(0.35)
Ever Migrated × Community Migration Network	−3.347**	−3.410**	−2.972**	−3.780**	−2.347**	−3.375**
	(1.69)	(1.65)	(1.45)	(1.73)	(1.15)	(1.69)

Note: Regressions also include individual and state-level controls as per tables 3 and 4. Robust standard errors in parentheses with standard errors clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Basic specification is for males 15 to 49, using ever migrated to the United States as the migration definition.

However, in strong network communities, where the cost of migrating is less binding, we find negative selection, which is what would be predicted by Borjas (1987) based on wage differentials. As a result, over time, as origin communities accumulate migration experience, one should expect to see a gradual worsening in the relative skill level of migrants. This finding is consistent with more aggregate evidence provided by Feliciano (2001), who finds a decline in the relative skill level of Mexican immigrants over the course of the twentieth century.

VI. Robustness

Table 5 examines the robustness of our main results to several alternative specifications. We focus on the sample of individuals in communities with population less than 100,000. Column 1 repeats the OLS and 2SLS results with and without municipal fixed effects for comparison with these alternate specifications. We begin by examining robustness to outliers in educational attainment. In less urban communities, 95% of males aged 15 to 49 have less than sixteen years of schooling, and 90% have less than twelve years. Columns 2 and 3 of table 5 therefore check that our results on educational self-selection are not being driven by outliers with postgraduate or university education, by top-coding schooling at sixteen years and twelve years, respectively. The results are very similar to our main results, with slightly stronger evidence of positive self-selection in small network communities when we top-code education at twelve years.

Second, in column 4, we show robustness to using the Mexican Census definition of a migrant, which is whether someone has migrated in the past five years. This classifies as nonmigrants individuals who have migrated before this time. We see similar qualitative results using this alternate definition, with a negative interaction effect. This effect is similar in magnitude to that using the ENADID migrant definition, except for OLS with municipal fixed effects, where the coefficient is smaller in magnitude and not statistically significant.

Third, our main analysis has concentrated on males aged 15 to 49. These are the prime working-age individuals who have been the focus of much of the debate in the literature about the direction of self-selection and are an age group where we are not concerned about bias caused by education-selective mortality. Nevertheless, in column 5, we show that the interaction effect continues to be negative and statistically significant when we consider all males age 15 and above, with no upper limit on age.

Fourth, as discussed in section III, one concern with the ENADID and other Mexico-based migration surveys is that they do not capture migrants who move with their whole families and are more educated on average than those who have family members remaining. The omission of such individuals is thus likely to bias against finding positive selection, since some highly educated migrants are not included in the regressions. To investigate the robustness of our results to this issue, we use the public use sample of the U.S. Census to obtain the educational breakdown of the 14.4% of recent male migrants who have migrated with their spouse present, and are hence least likely to be reported on from Mexico.[11] We then reweight the ENADID migrant sample so that it reflects the educational breakdown of both those in the ENADID and these individuals in the United States. Column 6 shows that this reweighting results in point estimates extremely similar to those in column 1, showing that the results are robust to this adjustment for undercount.

VII. Conclusion

We find that in communities with small migration networks, there is slightly positive, or neutral or intermediate, educational self-selection of migrants. This is consistent with high costs of migration being the determining factor of who migrates in these communities. In contrast, in communities with strong networks, where migration costs are lower, we find negative self-selection, consistent with lower returns to schooling in the United States than in Mexico. These results are found to be robust to the use of various definitions for migrants and to accounting for the undercount of some migrants in Mexican data.

Our results help in part to reconcile conflicting accounts of the direction of education selection among migrants from Mexico found in the literature. Since the direction of selectivity depends on the level of migration prevalence in a community, studies that estimate the average direction of selection will give different estimates if they draw on surveys from communities with differing levels of networks.

The results of this paper also suggest that as migration networks continue to develop, we should expect to see more negative educational selection of migrants from Mexico. However, given the concomitant rise in educational attainments throughout Mexico, this expected decrease in relative schooling levels does not necessarily imply a decrease in average schooling levels of future Mexican immigrants to the United States.

[11] The U.S. Census does not provide information on whether these individuals are coming from high- or low-migration networks. As we explain, our weighting procedure implicitly assumes that the unobserved individuals are drawn from communities in the same proportions as observed individuals. Given the relatively low level of undercount for males and the fact that our fitted probabilities do not change by much, we believe the general pattern of our results is also robust to alternative assumptions about the network these undercounted individuals are drawn from.

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DATA APPENDIX

TABLE A1.—DOES HISTORIC DEVELOPMENT PREDICT HISTORIC MIGRATION AND FIRST-STAGE RESULTS

		First-Stage Results	
	1924 State Migration Rate (1)	Migration Network (2)	Migration Network × Ever Migrate (3)
Historic development indicators			
Proportion of rural households owning land in 1910	−0.000152	0.00835	0.00033
	(0.00076)	(0.0058)	(0.0007)
Male school attendance rate in 1930	−0.000267	0.00155*	0.00016
	(0.00017)	(0.00082)	(0.0002)
Gini of household income in 1960	0.0184	−0.0317	−0.0126
	(0.018)	(0.1079)	(0.0140)
Gini of male schooling in 1960	−0.0184	0.3822*	0.0104
	(0.035)	(0.2182)	(0.0290)
Average male years of schooling in 1960	0.00580	−0.0086	−0.0095***
	(0.0038)	(0.0257)	(0.0030)
Instruments			
1924 state migration rate		8.167***	0.419**
		(0.896)	(0.197)
1924 State Migration Rate × Ever Migrated		−1.999	5.174***
		(1.488)	(1.675)
Observations	30	27,211	27,211
R^2	0.30	0.40	0.78
p-value for F-test that variables jointly 0	0.112		
F-test on instruments		41.57	24.51
Shea partial R^2		0.260	0.142

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the state level in columns 2 and 3. All columns also contain a constant. Columns 2 and 3 also include age group dummies and dummies for marital status and being a household head, population size dummies, and individual migration status. First-stage results in columns 2 and 3 are for table 4, column 5.

APPENDIX

PROOF OF PROPOSITION 1. The induced change in migration incentives, which we denote by Δ, is given by the difference between A and B: $\Delta = e^{\mu_\pi - \gamma_1 s} - e^{\mu_\pi - \gamma_1 s - \gamma_2 n} = e^{\mu_\pi - \gamma_1 s}[1 - (1/e^{\gamma_2 n})] > 0$, with $\partial\Delta/\partial n > 0$ and $\partial\Delta/\partial s < 0$.

PROOF OF PROPOSITION 2. To prove (a), note first that s_L and s_U are solutions of the following equation:

$$\mu_0 + \delta_0 s(n) = \mu_1 + \delta_1 s(n) - e^{\mu_\pi - \gamma_1 s(n) - \gamma_2 n}. \tag{A1}$$

Differentiating equation (A1) with respect to n, we have:

$$\delta_0 \frac{\partial s}{\partial n} = \delta_1 \frac{\partial s}{\partial n} + \left(\gamma_1 \frac{\partial s}{\partial n} + \gamma_2\right) e^{\mu_\pi - \gamma_1 s - \gamma_2 n},$$

and therefore

$$\frac{\partial s}{\partial n} = \frac{\gamma_2 e^{\mu_\pi - \gamma_1 s - \gamma_2 n}}{\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s - \gamma_2 n}}. \tag{A2}$$

The marginal effect of an increase in network size on the two critical schooling thresholds is therefore given by

$$\frac{\partial s_L}{\partial n} = \frac{\gamma_2 e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}}{\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}} \tag{A3}$$

$$\frac{\partial s_U}{\partial n} = \frac{\gamma_2 e^{\mu_\pi - \gamma_1 s_U - \gamma_2 n}}{\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s_U - \gamma_2 n}}. \tag{A4}$$

Note that having $(\partial s_L/\partial n) < 0$ and at the same time $(\partial s_U/\partial n) > 0$ requires $e^{\mu_\pi \gamma_1 s_U - \gamma_2 n} < (\delta_0 - \delta_1/\gamma_1) < e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}$. Combining equations (A3) and (A4), it is then straightforward to see that

$$\frac{|\partial s_L/\partial n|}{\partial s_U/\partial n} = \frac{\gamma_2 e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}}{|\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}|} \cdot \frac{\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s_U - \gamma_2 n}}{\gamma_2 e^{\mu_\pi - \gamma_1 s_U - \gamma_2 n}}$$

$$= \frac{e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}}{e^{\mu_\pi - \gamma_1 s_U - \gamma_2 n}} \cdot \frac{\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s_U - \gamma_2 n}}{|\delta_0 - \delta_1 - \gamma_1 e^{\mu_\pi - \gamma_1 s_L - \gamma_2 n}|} > 1,$$

which proves (a). Coupling this with the nonincreasing density assumption proves (b).