Where You Go Depends on Who You Know

Social Networks as
Determinants of Mexican Internal Migration

JEL classification: D85, F22, J15

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Second Year Paper

6 Sep 2022

Abstract: Recent qualitative evidence suggests that social networks play an important role in potential migrants' decisions to migrate and their choice of destination. Yet even the latest literature employing microeconomics migration models with social networks often only estimates these models on small household panel data sets. In this paper, I use the Mexican population census to estimate a structural gravity model with social networks on internal migration flows from origin municipalities to destination states over three recent five-year periods at the intensive and extensive margin. To proxy for the social networks, I use internal migrant flows along the same corridor in a previous time period. My results show that social networks affect migration flows. At the extensive margin, a 1% increase in the size of the social network increases by 5%, 12%, and 13% the likelihood of a migration corridor; at the intensive margin, the equivalent social network elasticities are 19%, 30%, and 32%. I identify the effects using origin and destination characteristics as well as the presence of a migrant flow in 1960 to control for other factors that could drive migration along these corridors. These results contribute to both microeconomic and macroeconomic analysis of the determinants of migration.

1 Introduction

Internal migration has overtaken birth and death as the primary source of demographic change at the regional level in many countries. In 2019, an estimated 763 million people worldwide lived outside the region in which they were born (UNESCO, 2018). Often internal migration plays an important role not only in population change but also in structural change, especially in the form of rural to urban migration. Yet despite the size and significance of this phenomenon, two important puzzles remain: who migrates and where?

In practice, internal migrants do not simply maximize the present value of two competing income streams, as Roy (1951) predicted. Nor does the introduction of self-selection by Borjas (1987) offer much clarity. In fact, breaking down migration trends by age and education only adds to the puzzle. In some situations, internal migration exhibits positive selection: the people who leave have the most to gain (Chiquiar & Hanson, 2005). In other situations, internal migration exhibits negative selection: the people who leave have the most to lose (Ibarraran & Lubotsky, 2007). These apparently contradictory results suggest that factors other than potential income gain play an important role in internal migration decisions.

Recent work has proposed that social networks at the destination may explain these seemingly contradictory results. McKenzie and Rapoport (2010) show that migrants are negatively selected in communities with a high proportion of outmigration and positively selected in communities with a low proportion of outmigration. Their work complements two other well-known studies of the effects of social networks on migration. Carrington et al. (1996) develops a model of endogenous moving costs to explain the internal migration destination choices of African-Americans in the 20th century of the United States. Munshi (2003) documents network effects in US-Mexico migration. In both cases, migrants in one time period tend to follow migrants from the same origin in previous time periods instead of simply seeking out the highest wages.

The present paper finds that social networks are positively associated with internal migration flows in Mexico from origin states to destination municipalities for men aged 25 to 55 from the Mexican population census in three recent five year intervals (1995-2000, 2005-2010, and 2010-2015). I examine this group of working age men as a sample that would be prone to migrate for work instead of education or family reunification. As a proxy for these men's social networks, I use the total number of people from the same origin state who migrate to the same destination municipality over the previous five year interval. The absence of flows from approximately 75% of the possible origin-destination pairs creates left censoring on the dependent variable. For this reason, I model the extensive and intensive margin of the men's internal migration as two distinct processes. The extensive margin refers to the opening, remaining open, or closing of potential migration corridors across the three time periods of interest. The intensive margin refers to the magnitude of the migrant that pass through these corridors at a particular time period.

At both margins, I estimate three models on these internal migration flows: a model with wage differences alone, a structural gravity model with wage differences, and a structural gravity model with wage differences and the social network proxy above. Adding additional covariates greatly increases the predictive power of the model. For a representative time period (1995-2000) at the extensive margin, differences in base wage and return to skill explain 2.5% of the variation at the extensive margin; a structural gravity model 26%; and a structural gravity model with social networks 39%. For the same time period at the intensive margin, differences in base wage and return to skill explain 5% of the variation; a structural gravity model 39%; and a structural gravity model with social networks 58%.

In addition, adding these additional factors first reduces and then eliminates the effect of the wage differences along a corridor on internal migrant flows. In the first model, wage differences are significantly associated with migration. In the second model, the association with wage differences decreases substantially but remains significant. In the third model, it decreases even more and loses significance. Moreover, the magnitude of the association increases across the three time periods. At the extensive margin, a 1% increase in the size of the social network is associated with a 4.6%, 11.9%, and 12.6% higher probability of the presence of a migration corridor, respectively, in the three time periods. At the intensive margin, the social network elasticities are 19%, 30.4%, and 31.9%. These empirical results show the importance of social networks in driving internal migration both at the extensive and intensive margins for the time periods in question.

Four aspects of this paper warrant further explanation because of their novelty. First, the novelty and the scale of my data source stand out as the first use of multiple waves of nationally-representative census data to examine internal migration with a structural gravity model augmented by social networks. The original article on the role of diasporas in international migration estimated a structural gravity model using cross-sectional data from 195 origin countries to 30 destination countries in the Organization for Economic Cooperation and Development (OECD) from 1990-2000 (Beine et al., 2011). Most previous work in Mexico and elsewhere has used small-scale panel data household surveys like the Mexican Migration Project, the Mexican Family Life Survey, or the National Survey of Rural Households (Cuecuecha & Pederzini, 2014; Durand & Massey, 2019). This work suggests that social factors have come to dominate economic factors over time (Asad & Garip, 2019). Even previous studies that estimated gravity models on Mexican census data did not include social networks in their models (Ochoa et al., 2018; Soloaga, Isidro et al., 2010). Thus this paper applies a frontier model to a large-scale data set: three waves of nationally representative Mexican census data.

Second, I follow Beine et al. (2011) in integrating the canonical models of migration from microeconomics and macroeconomics into a unified framework. In the applied microeconomics models of Roy (1951) and Borjas

(1987), potential migrants consider expected wage gain at the destination. In the present case and others, these models do not often fit the data well. In contrast, applied macroeconomics models the movement of people from one region to another in terms of the relative populations of the two regions and the distance between them using the same gravity model that it uses to model the movement of goods (Anderson, 2011). Gravity models often fit the data well but lack theoretical underpinning. The integrated model in the present paper begins with an individual considering two destinations; uses a multinomial logit to extend the choice to an arbitrary number of destinations; and then considers the probability of migration to each destination at the population level to estimate the migration flow from the origin to each destination. I include destination population, distance, indigenous share at origin and destination, and urban share at origin and destination as factors that affect migration flows. Because this structural gravity model is still relatively new in the literature, I offer a simplified derivation in section 2 based on Beine et al. (2016).

Third, I use auxiliary Mincer regressions at the state and municipality level to estimate the usual labor market parameters: base salary, return to skill, and return to experience. I drop return to experience because of the small magnitude. Instead of considering a representative worker (i.e. a 25 year old internal migrant with an elementary school education), and generating an average wage at origin and destination like Falaris (1987), I difference the base salary and return to skill parameters at the origin and destination to account for heterogeneity across geographical regions in the population of potential migrants. Intuitively, less educated rural to urban migrants may be influenced more by base salary differences, whereas more educated urban to urban migrants may be influenced more by differences in return to skill. These differences go into the model as proxies for wage differences between the origin and destination. To my knowledge, I am the first person to model counterfactual wage differences in this way.

Fourth, I use a new approach to the econometric challenge of identification of network effects. Here I use past migration flows as a proxy for social networks and examine their association with present flows. One concern is the possibility of serial correlation across time periods: unobserved time-invariant factors like individual preferences or cultural proximity that would affect both past and present migration flows along the same corridor. Previous literature has used rainfall shocks at the origin (Munshi, 2003) or railroads (Woodruff & Zenteno, 2007) as instruments to reduce the bias from this potential serial correlation. Instead, I use the presence of a migration flow in a given corridor in 1960 to control for "the taste for migration," non-economic factors that could influence the migration flow along a corridor. I justify the use of this control for both practical as well as theoretical reasons. The earliest Mexican census that asks about migration is from 1960. At this time, the structure of the Mexican economy was very different from the present day in several important ways. 1960 predates the end of the Bracero program of US agricultural visas (1964), the beginning of the maquiladora export manufacturing program (1964), the entry of Mexico into the General Agreement on Tariffs and Trade (1986), and the entry of Mexico into NAFTA (1994). Thus any migration corridors present in 1960 are due to either time-invariant cultural factors or economic factors proper to that period but not the time periods in question from 1995-2015. I argue that controlling for this taste for migration allows me to model only time-varying migration trends and estimate the effect of social networks on this migration. The inclusion of the migration taste factor decreases the associations and elasticities that I find above by at most 10%. This result suggests that the association of the social networks and migration flows does not come from unobserved time-invariant factors.

The results here matter not only in academic circles but also to policymakers who seek to accurately understand present and future migration trends. In the short term, receiving communities integrate new migrants into existing housing, jobs, schooling, and other programs. In many cases, NGOs assist with this integration. In the long term, destinations plan to adjust their infrastructure to account for future internal migration. Private enterprises as well benefit from information about future labor supply, since the population I study in this paper primarily moves for work reasons.

The paper proceeds as follows. Section 2 develops a theoretical model of migration flows from micro foundations to a structural gravity model with social networks. Section 3 gives additional background on internal migration and describes the data from the Mexican census. Section 4 describes the empirical method, including the Mincer models I use to estimate differences in base wage and return to skill. Section 5 presents the results: determinants of migration and social network elasticities at the extensive and intensive margin. Section 6 concludes.

2 Theoretical Framework

This paper uses a structural gravity model that unifies the canonical models of migration from microeconomics and macroeconomics. In this section, first I offer a conceptual overview of the simplifying assumptions required to consider migration in terms of expected wage gain, the monetary and non-monetary factors included in the cost of migration, and the proposed effect of social networks on reducing these costs. Next, I review the microeconomic migration model developed by Borjas (1987) and his discussion of positive and negative selection. Finally, I summarize the structural gravity model from Beine et al. (2011), which provides a bridge from a microeconomic model like that of Borjas to the gravity model that applied macroeconomics uses to analyze trade and migration flows. A key element of this paper's structural gravity model is the inclusion of social networks that reduce the cost of migration.

2.1 Conceptual Framework

Lucas (2021) describes the literature on rural-urban migration with a particular focus on the factors that affect migration flows and the effects of migration on origin and destination. His taxonomy of migration allows me to clarify the type of migration I will examine in this paper: potential migrants migrate when the income at the destination is higher than the income at the origin, taking into account the cost of migration. I make the following assumptions about potential migrants and their migration decisions.

1. Potential migrants decide to migrate purely based on economic reasons. This excludes other forms of migration, such as family reunification.

2. Potential migrants migrate permanently. This excludes seasonal migration or circular migration.

3. Potential migrants enjoy certain wages at the origin. This excludes the impact of uncertainty around agricultural production or potential risk aversion.

4. Potential migrants aspire to formal employment at the destination. This excludes informal employment at the destination.

5. Potential migrants always find jobs at the destination. This excludes the job search process or the possibility of unemployment or informal employment at the destination.

6. Potential migrants migrate based on a comparison between the income at the origin and the income at the destination.

A rich literature following Harris and Todaro (1970) has modeled rural-urban migration and the probability of obtaining a job in the formal sector at the destination. With the simplifying assumptions above, I sidestep this literature. Rather, the situations I consider align more with those considered by Banerjee (1991), who examines the case of migrants who migrate with a pre-arranged job. This approach matches that of Falaris (1987), who uses cross-sectional samples to pool movers and stayers across the possibility of multiple destinations within Venezuela, accounting for selection into migration but ignoring job search frictions and the existence of the informal sector.

Monetary gains not only come in terms of improved wages for the same occupation but also in terms of wage gains from occupational sorting. Previously Roy (1951) had proposed that individuals will choose the occupation that matches their endowment. He uses the example of occupational sorting into hunting and fishing. The endogeneity of this decision biases any attempt to estimate the effect of the occupation on the individual's income. Individual unobservables like ability could effect both the choice of occupation as well as the realized income.

Moreover, since a potential migrant considers lifetime earnings, different aged workers will approach the migration investment decision in different ways; for younger potential migrants, the potential return is larger than for older potential migrants, for example.

Within this framework of income comparison, potential migrants also consider the cost of migration. Sjaastad (1962) first introduced this notion of the cost of migration in his model, which treats migration as an investment in the migrant's own human capital. He considers two types of costs: monetary and non-monetary. Monetary costs include the cost of moving and the increase in cost of living at the destination. Non-monetary costs include the opportunity cost of lost wages while searching for a job and learning a new job; they also include the psychic cost of living away from family and friends.

Recent qualitative work has examined the role of social networks in migration, especially relative to these three costs. Garip and Asad (2016) outlines three channels by which social networks reduce the cost of migration: social facilitation, normative influence, and network externalities. Social facilitation refers to the way that past migrants reduce information frictions at the destination, reducing costs and increasing benefits, a phenomenon first identified by Yap (1977). Normative influence refers to the way that past migrants change social norms and make migration more attractive, also reducing the cost at the origin. Network externalities refer to how past migrants create a pool of common resources for future migrants.

Sociologists distinguish between the strong ties of family and friends and the "weak ties" of individuals from the same village or state (Granovetter, 1973). Davis et al. (2002) examines the effect of both types of ties on international and internal migration. In contrast, this paper only considers the effect of weak ties on internal migration.

2.2 Microeconomic Framework

Borjas (1987) offers a formal model of migration in terms of expected wage gain. Equations (1) and (2) decompose the expected wage for a resident of the origin or destination into an observed group mean and an unobserved disturbance. The indices 0 and 1 below indicate origin and destination. Intuitively, a given individual migrates when the gains, both observed or unobserved, outweigh the cost of migration: when the sign of the index function I below is positive.

$$\ln w_0 = \mu_0 + \epsilon_0 \tag{1}$$

$$\ln w_1 = \mu_1 + \epsilon_1 \tag{2}$$

$$I = \ln(w_1) - \ln(w_0) \tag{3}$$

Equation (5) introduces a cost of migration C. The ratio $\frac{C}{w_0}$ is the same for all individuals at the origin. The destination wages must exceed the origin wages plus the cost of migrating.

$$I > 0 \tag{4}$$

$$\ln(w_1) - \ln(w_0 + C) > 0 \tag{5}$$

$$\ln(w_1) - \ln(w_0) - \frac{C}{w_0} > 0 \tag{6}$$

$$(\mu_1 - \mu_0) + (\epsilon_1 - \epsilon_0) > \frac{C}{w_0} \tag{7}$$

Borjas' contribution is that not only the mean but also the variance of ϵ_i varies from the origin to the destination. He offers as one possibility a compressed distribution of $\epsilon_0 \sim N(0, \sigma_0^2)$ in an origin country with a low return to skill that expands to $\epsilon_1 \sim N(0, \sigma_1^2)$. Thus two potential migrants whose unobservable characteristics are nearly equivalent at the origin could see a larger difference at the destination, leading one to migrate and the other to stay. In fact, the location of an individual's unobserved characteristics in the distributions at the origin and the destination plays a key role in satisfying the migration condition above.

Borjas uses this model to consider the implications of different distributional assumptions of origin and destination unobservables.

1. Under positive selection, the best candidates migrate and outperform locals.

2. Under negative selection, below-average candidates can migrate, do worse than locals, but still earn more than at the origin, because their

native country has a more unequal income distribution.

3. Finally, under refugee selection, below-average individuals can migrate and outperform locals, because the income distribution is wider in the destination.

To account for these unobservable factors, a further model incorporates schooling into the wage equation at the origin and destination as follows.

$$\ln w_0 = \mu_0 + \delta_0 s + \epsilon_0 \tag{8}$$

$$\ln w_1 = \mu_1 + \delta_1 s + \epsilon_1 \tag{9}$$

Here δ_0 and δ_1 represent the return to schooling (or skill premium) at the origin and the destination respectively. Thus under a revised version of equation (7) above, individuals will migrate when

$$\ln w_1 - \ln(w_0 + C) > 0 \tag{10}$$

$$(\mu_1 - \mu_0) + (\delta_1 - \delta_0)s + (\epsilon_1 - \epsilon_0) > \frac{C}{w_0} \tag{11}$$

2.3 Structural Gravity Model

The microeconomic model above considers the decision to migrate at the individual level. This paper will consider migration flows between origin states and destination municipalities. To bridge the gap between the individual and the aggregate, I use the the structural gravity model. Beine et al. (2016)

provides a recent presentation of a structural gravity model developed from micro foundations and applied to migration.

The classical gravity model originated with Ravenstein's work studying migrant flows in the 19th century (Ramos, 2016). It has been applied successfully since then in many different contexts to the flow of goods and factors between countries (Anderson, 2011). Its empirical robustness owes to its parsimonious specification: the size of the origin, the size of the destination, and the inverse square of the distance between them. Recently available bilateral international migrant flow data has led to a renewed interest in the gravity model in studying migration. Nevertheless, until recently it was an "unconnected orphan" in the economics literature because of its lack of theoretical foundations. The structural gravity model addresses this deficiency by deriving an aggregate gravity model from an individual's decision to migrate in a framework in the microeconomic model above.

I begin with similar equations to (8) and (9) from the previous section. They consider the utility of an individual of type h staying in country i as $u_{ii}(h)$ and the same individual moving to country j as $u_{ij}(h)$. $C_{ij}(.)$ below is the cost of moving from country i to country j. I assume that it is constant for all individuals along the same migration corridor. This includes both the cost of moving as well as adapting to the destination.

$$u_{ii}(h) = w_i(h) + A_i + \epsilon_i \tag{12}$$

$$u_{ij}(h) = w_j(h) + A_j - C_{ij}(.) + \epsilon_j \tag{13}$$

The A_i and A_j terms are origin and destination characteristics that affect the desirability of living there. The error terms ϵ_i and ϵ_j are iid and follow an extreme value distribution.

Following a Mincer framework, an individual's schooling and experience will define his type h. I suppress the experience term to write the origin and destination wage equations as follows:

$$w_i(h) = \delta_i h + \mu_i + \epsilon_i \tag{14}$$

$$w_j(h) = \delta_j h + \mu_j + \epsilon_j \tag{15}$$

Now I use a multinomial logit model to extend this model from a single origin and destination to multiple destinations (indexed by k) and write the probability that a type h resident of country i will move to country j.

$$Pr\left[U_{ij}(h) = \max_k U_{ik}(h)\right] = \frac{N_{ij}}{N_i} = \frac{\exp[\delta_j h + A_j + \mu_j - C_{ij}(.)]}{\sum_k \exp[\delta_k h + A_k + \mu_k - C_{ik}(.)]} \tag{16}$$

In the same way, I can write the ratio of emigrants from country i to country j (movers) to residents of country i (stayers) as

$$\frac{N_{ij}}{N_{ii}} = \frac{exp[\delta_j h + A_j + \mu_j - C_{ij}(.)]}{exp[\delta_i h + A_i + \mu_i]} \tag{17}$$

Using logs, I next solve for the migration flow N_{ij} from location i to j by individuals of type h to obtain:

$$\ln N_{ij}(h) = (\delta_j - \delta_i)h + (A_j - A_i) + (\mu_j - \mu_i) - C_{ij}(.) + \ln N_{ii}(h) \qquad (18)$$

Next I will model the cost function $C_{ij}(.)$. Recalling the monetary and non-monetary costs outlined in the previous section, I include the distance between location i and j, both as a proxy for the initial monetary cost of travel and the psychic non-monetary cost of being away from one's friends and family.

An important element of the model I employ in this paper is is the inclusion of the social network in the cost function.

For this reason, I also include the stock of existing migrants M_{ij} from location i presently residing in j. Carrington et al. (1996) provides an early example of the this approach, which the authors term taking into account endogenous moving costs. They incorporate the stock of existing migrants in a given Northern destination state from a given Southern origin state into the cost function of a dynamic model of migration. In the international context, Beine et al. (2011) follows a similar approach and names the this stock of existing migrants in a given destination country from a given origin country the diaspora.

Both social networks and labor market conditions change over time, so I add a time dimension to the model. I assume that individuals who migrate in time period $[t-1, t]$ make a decision based on conditions at the beginning of the time period at moment $t-1$. With this addition, I arrive at the reduced form I will empirically estimate.

$$\begin{aligned}\ln N_{ijt} = (\delta_{jt-1} - \delta_{it-1})h + (\mu_{jt-1} - \mu_{it-1}) + M_{ijt-1} - \text{distance}_{ij} \\ + (A_{jt-1} - A_{it-1}) + \ln N_{it-1} + \epsilon_{ijt}\end{aligned} \tag{19}$$

Munshi (2020) also adds destination networks to a Roy-Borjas migration model and proposes that this addition generates two testable predictions for the augmented model.

1. Because the diaspora adds to the wage differential and subtracts from the cost of migration, potential migrants will reject higher wage differentials to follow the diaspora.

2. As the diaspora size increases over time, individuals from farther down the ability distribution choose to migrate.

In this paper, I will test both of these predictions.

3 Data

The principal data source for this paper is the Mexican population census conducted by the INEGI (National Institute of Statistics and Geography) and harmonized by IPUMS. In this section, I give background on Mexican internal migration, describe the three five year periods of interest, the subsample of interest (Working Age Men), the outcome of interest (migrant flow), an important additional variable (stock of internal migrants in 1960), and additional origin and destination characteristics that I use in the empirical model in (19).

3.1 Mexican Internal Migration

Despite a long history, internal migration within Mexico has received much less attention than US-Mexico migration. Mexican internal migration began to increase in the second half of the 20th century. The first wave in the 1960s coincided with the return of many agricultural workers from the US after the ending of the Bracero program. Martin (2020) gives more background on this program, which gave nearly 5 million temporary visas in a lottery to Mexican farm workers from 1942-64. During this period, many more Mexicans moved closer to the border in the hope of receiving visas in the lottery. Moreover, the international migration networks that this program established affected subsequent migration even after its termination. To create jobs for these return migrants, the Mexican government gave tax benefits to export manufacturing plants (maquiladoras) on the Mexican side of the border. Since the creation of this program, factories in ten border cities have emerged as prominent destinations for internal migrants (Hanson, 2001). The export manufacturing sector continued to grow as Mexico opened to foreign trade: its entry into the General Agreement on Tariffs and Trade in 1986 and the passage of the North American Free Trade Agreement in 1994. Chiquiar (2005) and Arends-Kuenning et al. (2019) show that Mexico's entry into GATT caused different regions to grow more quickly or slowly owing to preexisting physical and human capital endowments; the passage of NAFTA continued these trends. As a result of both events, export manufacturing benefited and internal migration increased toward more quickly growing areas, especially those with export manufacturing.

3.2 Periods of Interest

IPUMS harmonizes the decennial Mexican population census from 1960 to 2010, with the exception of the 1980 census, the records of which were destroyed by the 1985 Mexico City earthquake. Beginning in 1995, the INEGI began to conduct a quinquennial census as well, and IPUMS also has harmonized this census for the years 1995, 2005, and 2015. Thus I have five candidate five year intervals: 1990-1995, 1995-2000, 2000-2005, 2005-2010, and 2010-2015. I exclude two of these intervals.

1990-1995 As the subsequent tables and maps indicate, the 1995 census had a much smaller sample than subsequent decennial or quinqennial censuses so I cannot use it to construct $flow_{1995-2000} = stock_{2000} - stock_{1995}$. In addition, the devaluation of the peso, the Zapatista uprising in Chiapas, and the passage of the North American Free Trade Agreement creates an idiosyncratic shock in this period.

2005-2010 I omit the 2005-2010 interval because the 2005 census did not include the employment module that I use to generate counterfactual wage predictions that I describe in the subsequent section.

Thus I conduct the analysis over three intervals: 1995-2000, 2000-2005, 2010-2015. Like many other censuses, the Mexican census uses stratified sampling along several demographic characteristics. Individual entries have individual population weights and household population weights. In accordance with the guidelines in Solon et al. (2015), I use the individual population weights for the descriptive statistics below and for the Mincer regressions I estimate in section 4.1.

3.3 Sample of Working Age Men

This paper estimates the effects of social networks on a particular sample of internal migrants: men from age 25 to 55, a group we call Working Age Men. In this subsection, I explain the choice of this sample using the 2000 census.

As I discuss in section 2, this paper's theoretical model considers migration as an investment decision in a human capital framework in which the potential migrant seeks to maximize lifetime earnings. Not all migrants move to maximize earnings, however. Some move to attend school or to follow family members.

In order to estimate the additional explanatory power of social networks over wage differences in determining migration destinations, I would like to choose a sample that would be particularly prone to migrate for work and thus sensitive to wage differences. Using this subset would put a upper bound on the effect of wage differences and a lower bound on the effect of social networks. I will use the 2000 census to justify the sample because of its completeness and a unique question was only asked in this year: the reason for migration. Table 1 summarizes their results by share of internal migrants.

Migration Cause	Women	Men	Working Age Men	Total
Unknown	14.632	12.725	7.779	27.357
Seeking work	8.251	13.028	7.864	21.279
Family move	9.159	6.232	3.572	15.392
Other reason, not elsewhere classified	6.225	5.576	3.850	11.801
Job relocation	3.494	6.932	5.667	10.426
Marriage or union	5.036	1.857	1.425	6.893
Study	1.802	2.019	0.536	3.821
Violence or insecurity	0.802	0.727	0.506	1.529
Health	0.805	0.698	0.483	1.503
Total	50.205	49.795	31.681	100.000

Table 1: Reason for Migration for Individuals Aged 16-65 (2000 Census)

First, though an almost identical number of men and women migrate, men are almost twice as likely to migrate for work than women (the reasons "seeking work" and "job relocation"). Thus I will restrict the sample to men.

Again using the 2000 census, I examine the share of male internal migrants by age in figure 1. This graph gives an empirical estimate of the probability of migration conditional on age. At each end of this interval, the decision to migrate for work is one of a set of options working locally (through the interval), additional education (at the lower bound), and retiring (at the upper bound). I would like to choose a interval that minimizes the probability of these two other decisions.

To choose the the lower bound of this interval, I consider the probability of education conditional on age in Figure 2. At age 20, 25% of men are still in school; by age 25, this share has dropped to 9%.

To choose the upper bound of the interval, I consider the probability of retirement conditional on age in Figure 3. At age 65, 13% of men have decided to retired; at age 55, this share has dropped to 3%.

Thus I restrict the sample to men to minimize the impact of the decision to migrate for non-work reasons and from 25 to 55 years old to minimize the impact of the decision to pursue additional education or retire.

I consider one final selection issue in the sample: the decision to select into labor. Figure 4 shows the share of unemployed men by age. This share is at most 2% for a given age cohort. These results suggest that most men who want can find employment, in either the formal or informal sector.

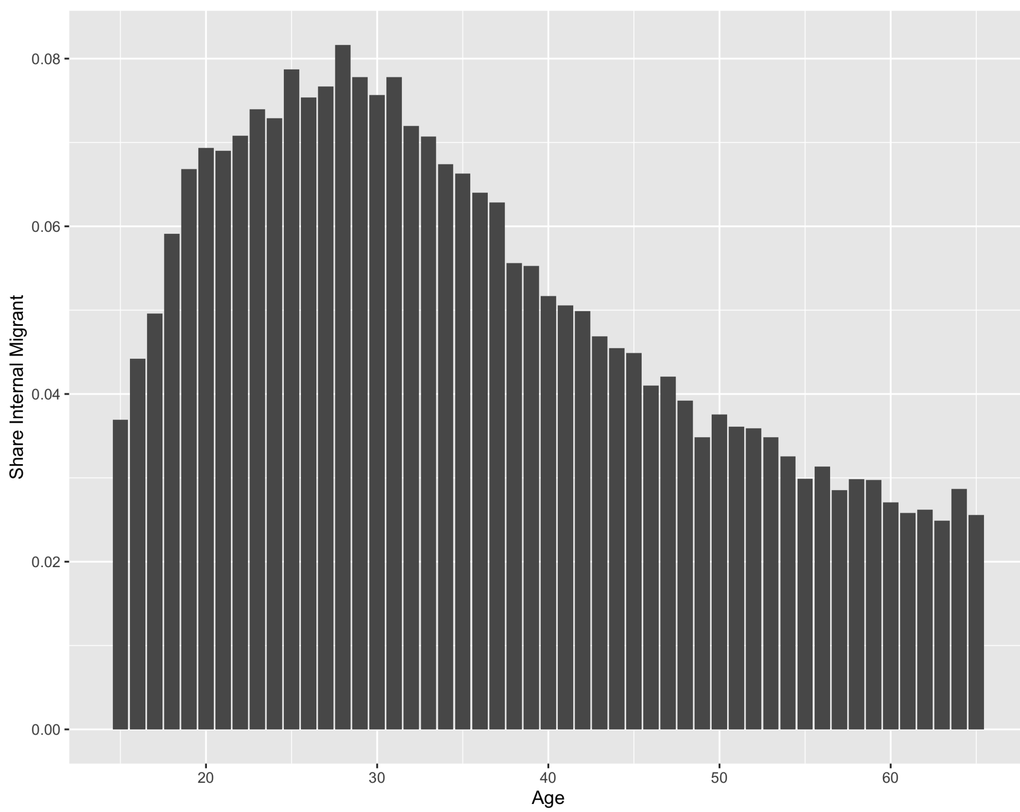

Figure 1: Share of Male Internal Migrants by Age (2000)

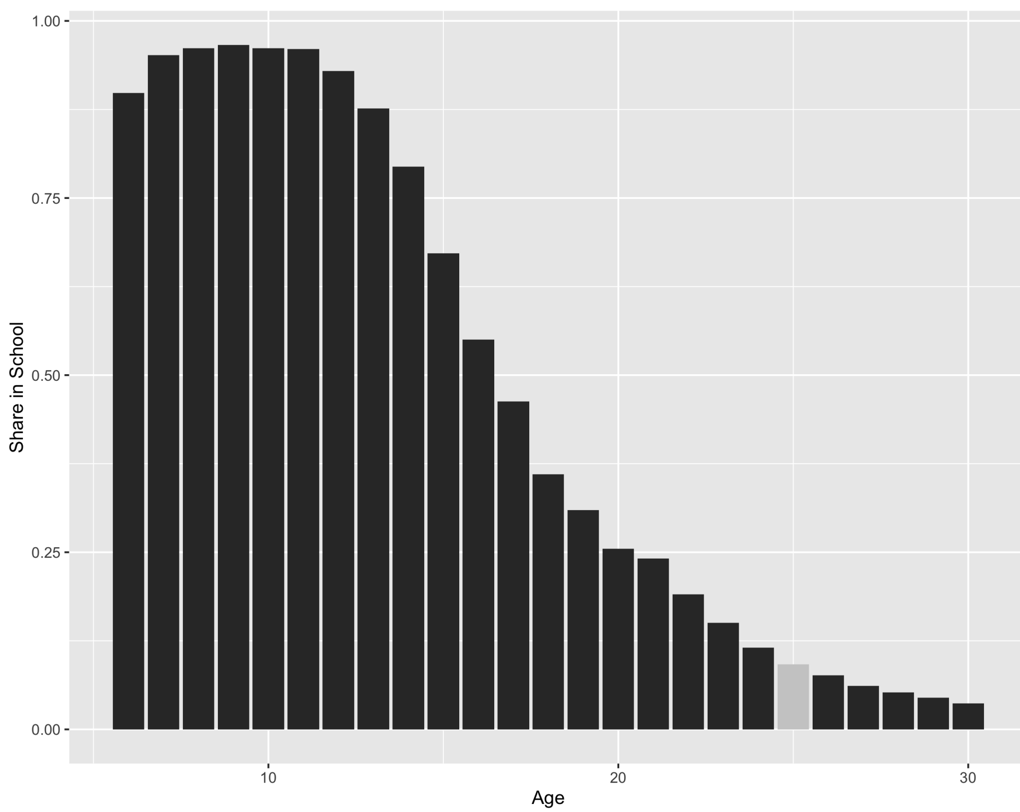

Figure 2: Share of Males in School by Age (2000)

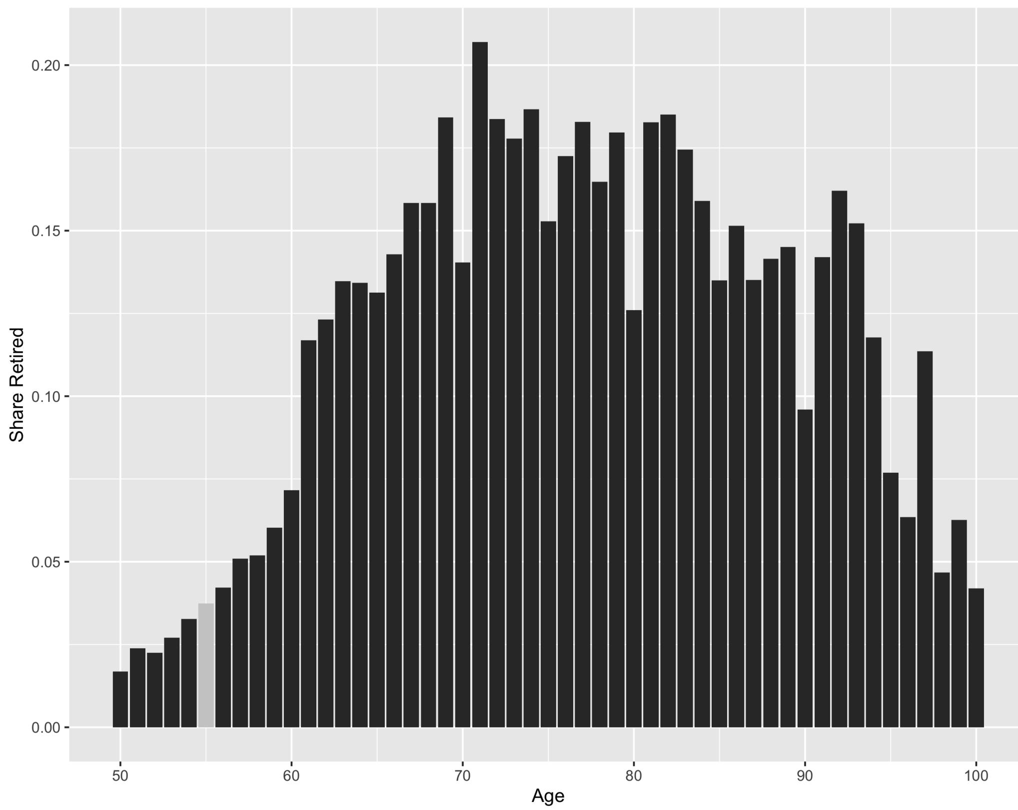

Figure 3: Share of Males Retired by Age (2000)

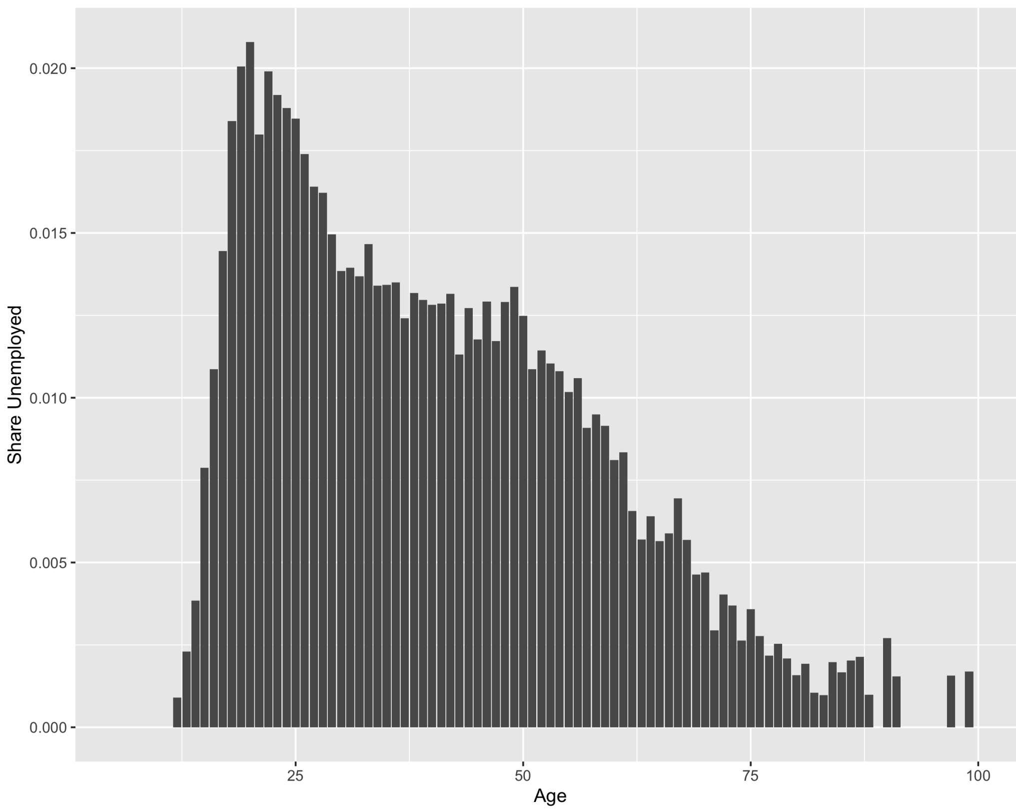

Figure 4: Share of Males Unemployed by Age (2000)

The rightmost column in Table 1 shows the migration reasons of our Working Age Men sample. 44% report migration for work reasons.

I conclude my description of the Working Age Men sample with two final comments. First, the migration cause question has many limitations. Only the 2000 census asks the question and almost 40% of the responses are "Other reason" or "Unknown". It serves at best as only a rough guide to choosing the appropriate sample for this analysis, even when we supplement it with employment, retirement, and schooling profiles by age.

On the other hand, the analysis of this paper does not depend entirely on finding a sample of individuals whose choice set consists only of working locally or migrating for work reasons. It merely examines the extent to which social networks add additional explanatory power to other reasons why individuals migrate, especially wage differences. For this reason, I use a subsample particularly sensitive to wage differences.

3.4 Summary Statistics of Working Age Men

Table 2 shows summary statistics for the population of Working Age Men in each census: income, age and schooling. I compute experience in the typical way (age - schooling - 6) to use in the Mincer regressions we will describe in section 4.1. Labor Force Participation (LFP) is above 90% in all intervals. The key variables of schooling and income are present for the vast majority of the sample.

Unlike other censuses, the Mexican census asks several questions about income: earned income, income from pensions, income from government support programs. I use "earned income", which is defined as monthly income in pesos. In addition, the table shows the percentage who are internal migrants.

Through the five censuses, mean income, age, and schooling increase. Income and schooling increase as a result of Mexico's economic development. The age increase shows the demographic changes of an aging population.

Table 3 shows a decomposition by cohort of the Working Age Population with the population shares of each cohort as well as the LFP and the internal migration shares. The age distribution shifts slightly older from 1995 to 2015. LFP peaks in the 35-39 cohort but is above 90% in almost all cells except in the final five year interval. Internal migration is highest for the youngest cohort and steadily decreases. This empirical fact is typical of rural-urban migration in developing countries (Lucas, 2021).

		Shares				Income		Age		Schooling		Experience	
Year	Total	LFP	School	Income	Migrant	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1995	14875665	0.949	0.994	0.951	0.066	1602.962	23.858	36.624	0.058	7.845	0.037	22.779	0.075
2000	16497274	0.917	0.971	0.964	0.061	3597.730	12.014	36.908	0.008	8.306	0.005	22.602	0.010
2005	18472940	NA	0.973	NA	0.042	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2010	20775439	0.931	0.989	0.929	0.068	6035.489	20.827	37.909	0.014	9.333	0.009	22.576	0.017
2015	22747904	0.911	0.997	0.918	0.053	7240.150	19.833	38.198	0.012	10.280	0.009	21.918	0.015

Table 2: Working Age Men Overall by Year

	Share				Working				Int Migrant			
Cohort	1995	2000	2010	2015	1995	2000	2010	2015	1995	2000	2010	2015
25-29	0.243	0.235	0.199	0.194	0.946	0.909	0.912	0.891	0.082	0.078	0.087	0.067
30-34	0.211	0.207	0.192	0.186	0.961	0.933	0.944	0.929	0.084	0.073	0.087	0.066
35-39	0.187	0.185	0.189	0.179	0.963	0.934	0.949	0.930	0.063	0.061	0.072	0.057
40-44	0.146	0.153	0.162	0.172	0.952	0.927	0.943	0.924	0.057	0.049	0.059	0.048
45-50	0.118	0.120	0.139	0.142	0.945	0.908	0.932	0.911	0.041	0.041	0.048	0.038
50-54	0.096	0.101	0.119	0.127	0.906	0.866	0.893	0.874	0.040	0.036	0.038	0.033

Table 3: Working Age Men by Cohort

3.5 Outcome of Interest: Migrant Flow

Mexico is divided into 32 federal entities (31 states and the federal district of Mexico City). For simplicity I refer to the entities below as states. Each state is divided further into municipalities.

The census asks about migration in two different ways. In 1960, it asks if individuals presently residing in a given municipality have moved from another state during their lifetime. In the 1990 and subsequent Mexican censuses, individuals presently residing in a particular municipality report their state of residence five years ago.

By totaling the number of residents of a municipality who were born in another state (in the case of 1960) or who lived in a different state five years ago (in the case of the other time periods), I can construct a measure of a possible internal migration corridor originating in one state and terminating in a municipality in another state. This method omits both temporary migrants as well as migrants who lived in a third location, either within Mexico or abroad, in the intervening five years.

With this definition, the three intervals of interest, I compute the migrant flow in the period $[t-1, t]$ from origin state s to destination municipality m and denote it as $flow_{smt}$. As a point of comparison, I also compute the internal migrant stock in 1960, $flow_{1960}$.

Table 4 provides information about the internal migrant flows in each of the three periods of interest as well as the internal migrant stock in 1960. The Destinations column indicates the number of municipalities surveyed in the census. The Possible Flows column multiplies Destinations by 31 to indicate the number of potential migration corridors that could be captured. The Active Flows indicates the number of migration corridors that were actually captured.

The number of possible flows is increasing across time periods for two reasons. First, the number of municipalities is increasing. As of 2021, there are 2471 municipalities. Second, the coverage of the Mexican census is improving.

Computing the flows this way allows me to detect $32 \cdot 2471 = 79072$ origin-destination combinations. Since I do not consider migrations within the same federal entity, I can remove 2471 of these combinations, placing an upper bound of 76601 detectable migrant flows. The number of flows in the last time period approaches this upper bound.

A central empirical question of this paper is whether migration from a particular origin state to a destination is associated with further migration along the same corridor in subsequent time periods. Thus the first set of columns compares migration corridors from the three periods of interest to to the corridors open in 1960 and the two subsequent sets of columns compare the second and third period of interest to the first and the third to the second, respectively. In all cases, the Stay and Closed columns in these comparison columns adds up to the Active Flows column for the reference period; the Stay and Opened columns adds up to the Active Flows column from the current period.

		Flows		Compared to 1960			Compared to 1995-2000			Compared to 2000-2005		
Period	Dest	Possible	Active	Stay	Closed	Opened	Stay	Closed	Opened	Stay	Closed	Opened
1960	252	7812	4195	NA	NA	NA	NA	NA	NA	NA	NA	NA
1995-2000	627	19437	6654	2263	1932	4391	NA	NA	NA	NA	NA	NA
2000-2005	1978	61318	10052	2707	1488	7345	4286	2368	5766	NA	NA	NA
2010-2015	2309	71579	17307	2873	1322	14434	4715	1939	12592	7223	2829	10084

Table 4: Summary of Migrant Flows by Period

Figures 5, 6, and 7 show the logged flow of internal migrants by destination municipality for each of the three intervals in question.

3.6 Origin and Destination Characteristics

The theoretical model that I developed in the previous section also includes origin and destination characteristics that could affect the desirability of migration. For each of the three time periods of interest, I use the value of the characteristic from the start of the time period.

Population I compute the population of a state or municipality by using the total number of people in the most recent decennial census. Figure 8 shows the logged municipal population at year 2000.

Indigenous Share I compute the indigenous share for a state or municipality using the number of people in the most recent decennial census who report being indigenous. I divide this number by the population. The 1990 census does not ask this question, so I do not include this characteristic for that time period. Figure 9 shows this share.

Urban Share I compute the urban share for a state or municipality using the number of people in the most recent decennial census who report living in an urban area. I divide this number by the total population. Figure 11 shows this share for the year 2000.

Border Potential migrants could migrate to the border as a destination as a first step toward migration to the US. In a similar way, migrants recently deported from the US could originate at the border. I assign a dummy

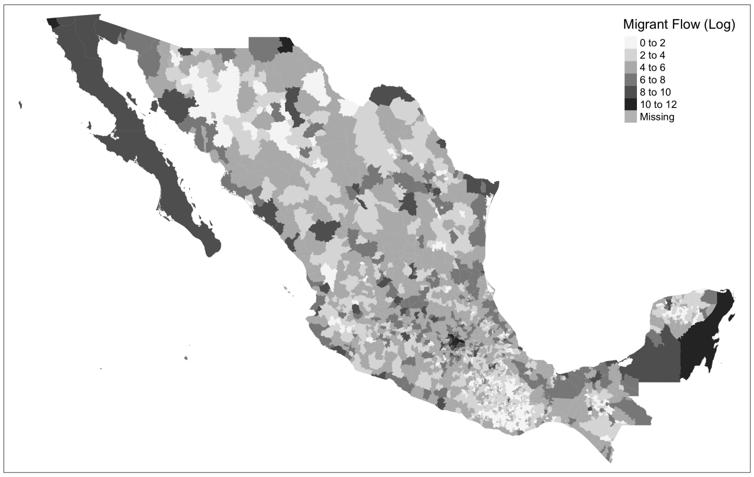

Figure 5: Internal Migration Flow from 1995-2000

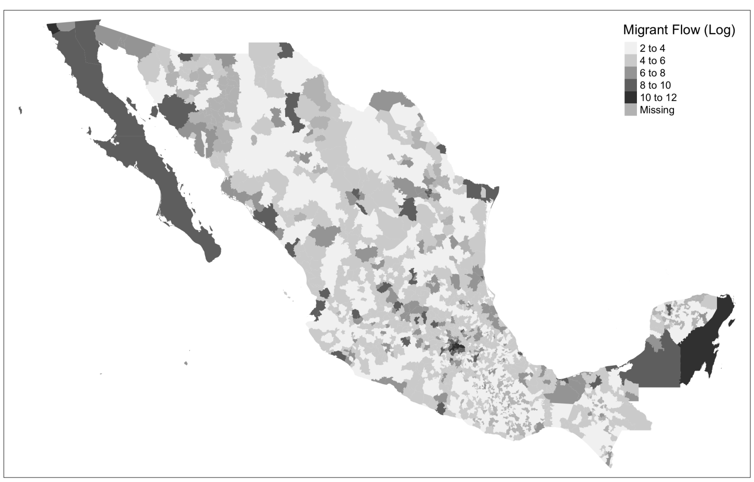

Figure 6: Internal Migration Flow from 2000-2005

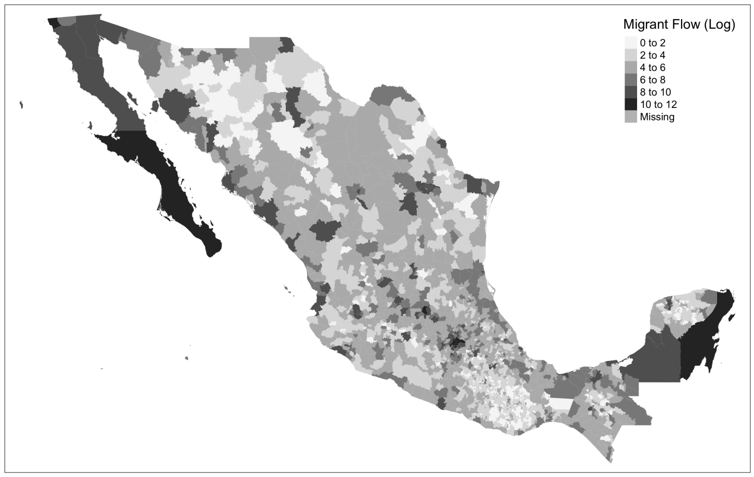

Figure 7: Internal Migration Flow from 2010-2015

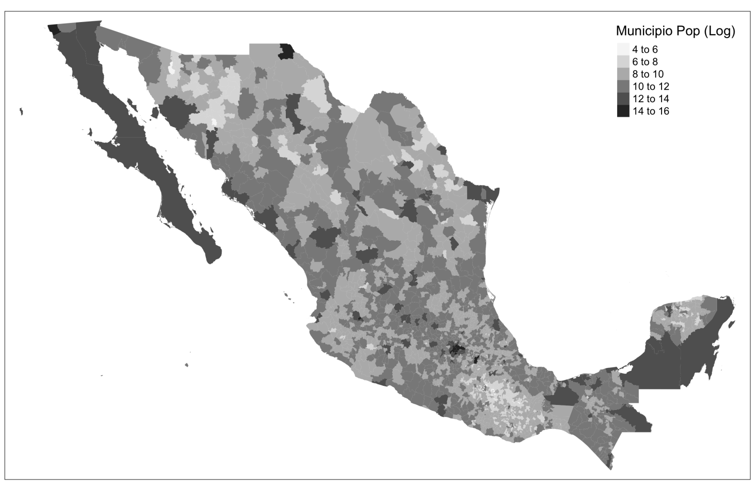

Figure 8: Municipality Population (2000)

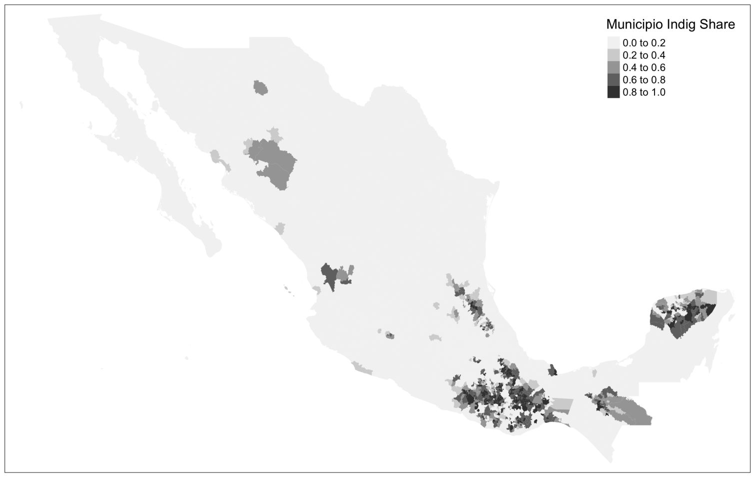

Figure 9: Municipality Indigenous Household Share (2000)

Figure 10: Border Municipalities

variable to all origin and destinations on the US/Mexico border. Figure 10 shows border municipalities.

Distance. IPUMS provides shapefiles for all Mexican states and municipalities. I compute the $distance_{sm}$ as the distance between the centroid of s and the centroid of m.

4 Empirical Framework

Here I describe in detail the empirical method I use to estimate the structural gravity model that I develop in the previous section, concluding with equation (19). First, I describe the auxiliary Mincer regressions that I use to estimate the labor market difference parameters. Second, I describe how I estimate the main model, the effect of social networks on the migrant flow $flow_{smt}$ from a state to a municipality at a given time period. I use OLS to estimate separately the extensive and intensive margin to account for the possibility of left censoring in $flow_{smt}$. Third, I describe a potential threat to identification, the presence of time-invariant factors that could affect migrant flows across multiple time periods. I propose the use of the presence of a migrant flow along the same corridor in the year 1960 to control for this possibility, which I call a "taste of migration." Finally, I discuss inference issues and the use of clustering at the destination state level.

4.1 Labor Market Differences

I do not use population weights for the main regressions here. and for the Mincer regressions I describe in section 4.1.

Both Falaris (1987) and Beine et al. (2011) use average wage at the destination to capture the effect of wage differential on migration. Using only the mean wage, however, omits the heterogeneous effects of varying levels of schooling and experience on an individual's decision to migrate. As table 2 indicates, average education level changes across the time periods of interest. Moreover, the effect of the difference in return to skill could vary depending on the presence of positive or negative selection, as I describe in section 2.1.

In order to capture the expected wage differential in a flexible way that accounts for this heterogeneity, I suppress the h from the theoretical model and instead incorporate $\mu_j - \mu_i$ and $\delta_j - \delta_i$ directly into the empirical model. I denote these differences as $\tilde{\alpha}$ and $\tilde{\beta}$ respectively. Note that in the case of internal migration origin country i becomes origin state s and destination country j becomes destination municipality m.

$$\mu_{jt} - \mu_{it} = \alpha_{mt} - \alpha_{st} = \tilde{\alpha}_{mst} \tag{20}$$

$$\delta_{it} - \delta_{it} = \beta_{mt} - \beta_{st} = \tilde{\beta}_{mst} \tag{21}$$

Now I must estimate $\tilde{\alpha}_{mst}$ and $\tilde{\beta}_{mst}$. To do this, I use Mincer equations for the Working Age Men in each state s and municipality m at the beginning of each time period $t \in \{1995, 2000, 2010\}$. As I describe in the previous section, I use "earned income in the past month" as the income variable and exclude elements of the sample with unknown education levels and income.

I estimate the parameters of a Mincer regression separately on each state and municipality in Mexico for the three time periods of interest and store the α and β coefficients.

$$\log(\text{income}_{tmi}) = \alpha_{tm} + \beta_{tm}\text{educ}_{tmi} + \gamma_{tm}\text{exp}_{tmi} + \delta_{tm}\text{exp}_{tmi}^2 + \epsilon_{tmi} \quad (22)$$

$$\log(\text{income}_{tsi}) = \alpha_{ts} + \beta_{ts}\text{educ}_{tsi} + \gamma_{ts}\text{exp}_{tsi} + \delta_{ts}\text{exp}_{tsi}^2 + \epsilon_{tsi} \quad (23)$$

For these parameters, m indexes the municipality, s indexes the state, and i indexes the individual within the municipality or state. The α_{tm} and α_{ts} parameters represent the base salary of the origin state and destination municipality. The β_{tm} and β_{ts} parameters represent the return to skill at origin state and destination municipality.

Figures 12, 13, and 14 show the logged base salary at the beginning of the three time periods in question. Figures 15, 16, and 17 show the skill premium at the beginning of the three time periods in question.

I find little cross-sectional variation in the γ and δ parameters related to the return to experience, so I do not include them in the model.

As table 2 indicates, the small sample size of the 1995 census results in the inability estimate labor market parameters for some municipalities, which appear in grey in the associated maps.

Using these estimates, I compute the parameter differences for each com-

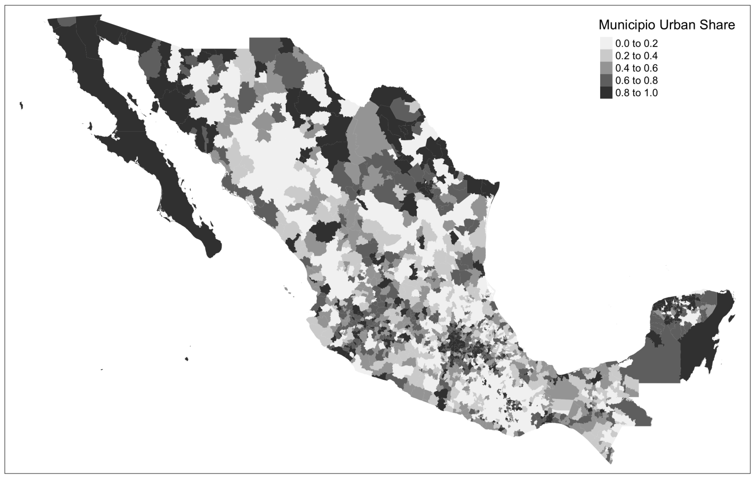

Figure 11: Municipality Urban Household Share (2000)

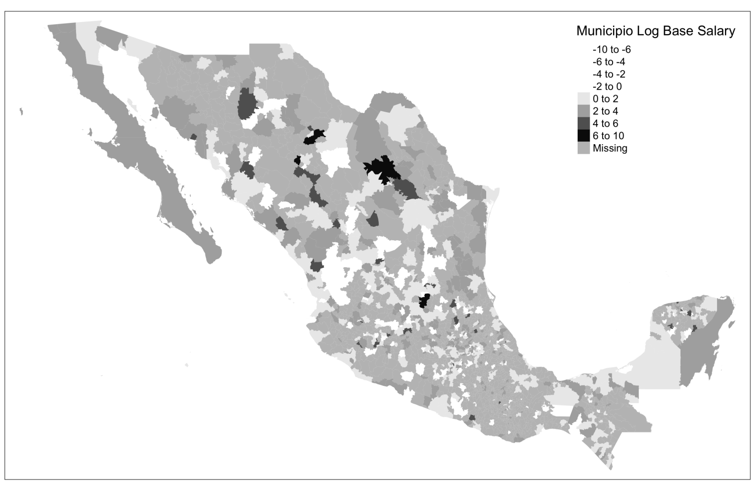

Figure 12: Logged Base Salary by Municipality (1995)

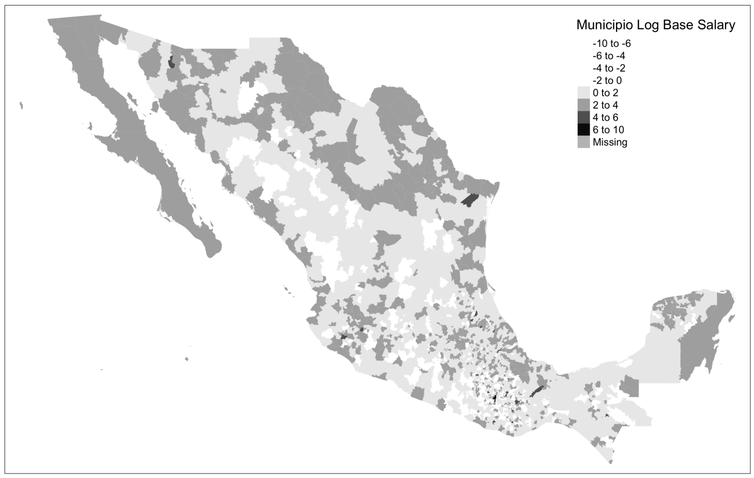

Figure 13: Logged Base Salary by Municipality (2000)

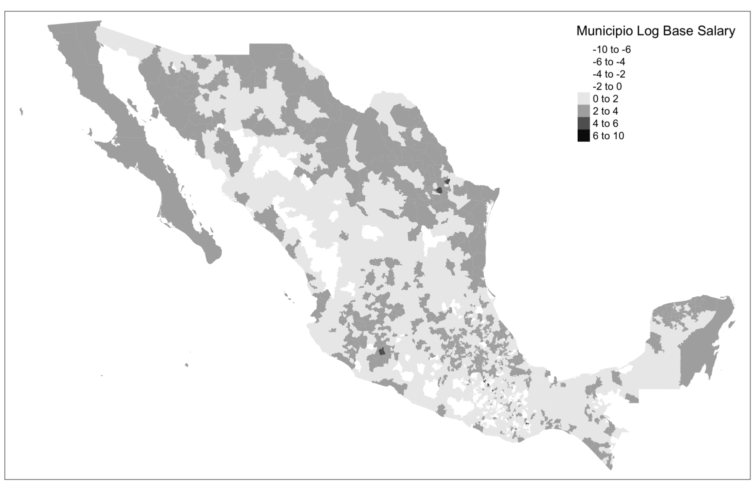

Figure 14: Logged Base Salary by Municipality (2010)

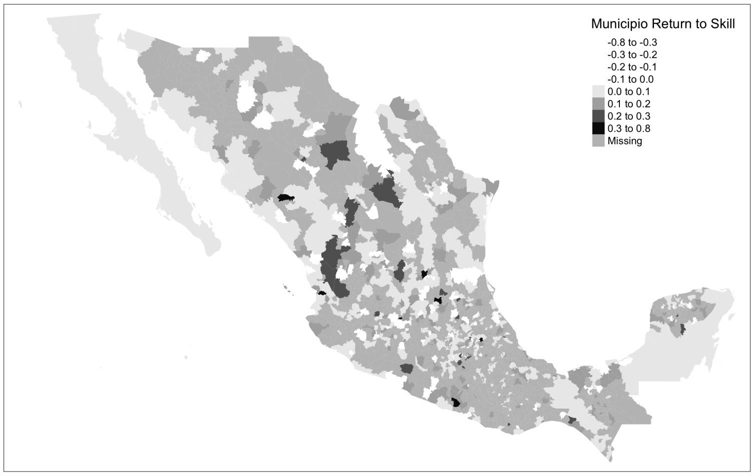

Figure 15: Return to Skill by Municipality (1995)

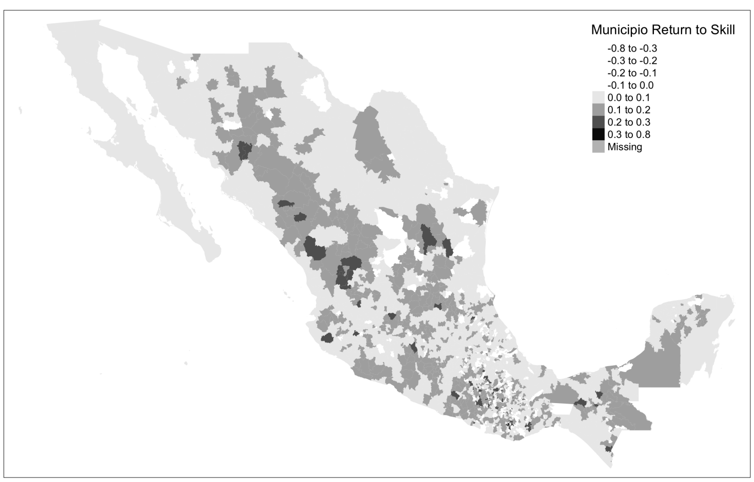

Figure 16: Return to Skill by Municipality (2000)

bination of origin state and destination municipality in each of the three time periods. I use these values in the estimation of the main model below.

$$\tilde{\alpha}_{smt} = \alpha_{tm} - \alpha_{ts} \tag{24}$$

$$\tilde{\beta}_{smt} = \beta_{tm} - \beta_{ts} \tag{25}$$

4.2 Estimation

Recall that I consider aggregate migrant flows $flow_{smt}$ from a Mexican state s to a Mexican municipality m in five year intervals $[t-1, t]$. Section 2.1 gives more detail on this definition of internal migration and section 3.5 gives more information about these particular migrant flows.

I begin with equation (19) as follows:

$$\begin{aligned} \log(\text{flow}_{smt}) = \delta_0 + \delta_1 \tilde{\alpha}_{smt-1} + \delta_2 \tilde{\beta}_{smt-1} \\ + \delta_3 \text{flow}_{smt-1} + \delta_4 \text{distance}_{sm} + \gamma A_s + \phi A_m + \epsilon_{smt} \end{aligned} \tag{26}$$

Here I use $flow_{smt}$ as N_{ijt}, the number who migrate from country i to country j at time period t. I use $flow_{smt-1}$ as M_{ijt}, the size of the diaspora from country i already present in country j at time t.

Recall that A_s and A_m are vectors of other origin state and destination municipality characteristics that could influence migrant flow. I populate them with three characteristics: urban share at $t-1$, indigenous share at $t-1$, and presence on the US/Mexico border. In addition, to match the

$log(N_{it-1})$ term in the model, I include the population of the origin state in A_s.

4.2.1 Extensive and Intensive Margins

As table 4 indicates, an econometric challenge to estimating equation (26) is the presence of zero flow values: 66%, 84%, and 76% respectively in the three time periods of interest.

This issue is not unfamiliar in the gravity model literature. Beine et al. (2011) uses two-stage Heckman estimators as a robustness check on OLS estimates of a model very similar to ours. The intuition behind the Heckman estimator is that two separate processes are operating: the first selects into or activates a migration corridor and the second determines the magnitude of the flow through it. Treating these processes as one risks biasing the estimated effect of the treatment, in this case the social network.

The Heckman estimator corrects for selection bias: the same factors that affect the presence of a migration corridor could also affect the flow through that some corridor. Here I am interested in examining the presence of a migration corridor as a process in its own right. For this reason, I estimate separately the extensive and intensive margin of the effect of social network on migration flows.

The extensive margin refers to the effect of the social network on whether a corridor opens or remains open during a time period. I define a new dependent variable $flowpresent_{smt} = 1[flow_{smt} > 0]$ as an indicator that takes the value of 1 if there are internal migrants from state s residing in municipality m at time t and 0 otherwise. I will estimate a version of equation (26) above with this new indicator variable.

To perform this estimation, I use an Linear Probability Model for two reasons. First, very few of the predicted values are out of the $[0, 1]$ range, so I see no advantage to a logit or probit model. Second, I can directly interpret the coefficients of the LPM in the subsequent results section. The coefficient of interest is δ_3, the effect of the social network on the presence of a flow.

$$\begin{aligned} \text{flowpresent}_{smt} = \delta_0 + \delta_1 \tilde{\alpha}_{smt-1} + \delta_2 \tilde{\beta}_{smt-1} \\ + \delta_3 \text{flow}_{smt-1} + \delta_4 \text{distance}_{sm} + \gamma A_s + \phi A_m + \epsilon_{smt} \end{aligned} \tag{27}$$

I estimate equation (27) on the entire sample. For the subsample for which $flowpresent_{smt} = 1$ at each time period, I estimate equation (26) to obtain the intensive margin.

The estimation technique in this paper differs from other literature that uses gravity models to estimate migration flows. First, many authors use the Pseudo-Poisson Maximum Likelihood Model developed by Silva and Tenreyro (2006) to account for potential bias in the effect of determinants of migration because of the censoring on the dependent variable. Because I estimate these margins separately, we do not use this estimator. Neither does Beine et al. (2011).

Second, even though I could construct a panel data set of our state-municipality migrant flows across the time periods of interest, I do not, because we expect the effects of the determinants of migration to vary over time. As section 3.1 describes, I would like to see the effect of the structural changes of the Mexican economy and the changing value of the outside option of migrating to the US on the estimated effects of the various determinants of migration in our model in our time periods of interest. In particular, I would like to see if the effect of social networks changes over time.

4.3 Identification

Identifying network effects poses statistical challenges. In this section, I group these challenges in two categories: across space (the way that the relative desirability of one destination influences another in the same time period) and time (the way that the patterns of migration in one time period affect migration in a subsequent time period through the channel of social networks). Both types of challenges relate to SUTVA (the Stable Unit Value Treatment Assumption) described in Morgan and Winship (2014) and elsewhere.

First, I consider the challenges across space. In the multinomial logit model that I develop in section 2, potential migrants do not simply choose to stay or leave; instead, they choose among a variety of destinations. In the aggregate setup here, each unit is a potential migration corridor from an origin state to a destination municipality. The treatment is the magnitude of the migration flow along the same corridor from the previous time period. For SUTVA to hold, the treatment received by one unit must have no relationship to the treatment received by another unit across space or time In other words, the migrant flows along a given corridor in the previous time period $flow_{smt-1}$ must be unaffected by the migrant flow along other corridors $flow_{-s-m-1}$ in the same previous time period.

This statement is not true. In a given time period, the migration decisions of the population of Working Age Men in a given state satisfies a population balancing equation: the number of men who do not migrate plus the number of men who migrate to each destination must sum to the total population of the state. Intuitively, the sums are related in this way: increasing the social network in one potential destination municipality decreases the size of the social network in another potential destination municipality. Thus the strong form of SUTVA does not hold in this case.

In fact, changing the distribution of the destination municipalities of migrants from the same origin state in a previous period affects the relative desirability of those destinations in the current time period. The relevant question is the relative magnitude of these effects. I argue that these effects are so small as to not warrant consideration because they are so diffuse. From a given state, a potential migrant considers nearly 2000 destinations. In a given time period, 10% to 20% of these destination corridors are open: 200 to 400 destinations. The decision of one migrant would seem not to affect the decision of another migrant very much.

Recent literature in biostatistics has developed techniques to address this particular relaxation of SUTVA, a situation of allocation of a common resource where the treatment status of each unit affects the treatment status of every other unit (Miles et al., 2019). Further analysis could apply these techniques to the present situation to empirically verify this intuitive argument.

Next, I consider challenges across time. As Manski (1993) and Munshi (2020) point out, identifying network effects poses statistical challenges. In this case, since I am estimating the effect of $flow_{smt-1}$ on $flow_{smt}$, a serially correlated shock across two time periods could generate a spurious correlation between the flows.

One approach would use an instrumental variable to estimate the effect of $flow_{smt-1}$. In the Mexico-US context, two authors use exogenous shocks at the origin: rainfall (Munshi, 2003) and the presence of railroad networks (Woodruff & Zenteno, 2007). In the European context, Beine et al. (2011) use three different instrumental variables: diplomatic representation of one country in another, the presence of a guest worker program, and conflicts in the origin country. Munshi (2020) also discusses the possibility of exploiting variation in network quality or conditions at the destination. By using an instrument correlated with origin conditions but not destination conditions, all of these approaches hope to correct for any serially correlated shock.

This paper proposes a different approach: a simple model of a taste for migration. A taste for migration between an origin and a destination is a factor such as a common climate or cultural connection that the model here does not account for. The simplest version of such a taste would be a time-invariant dummy variable between an origin-destination pair. A more sophisticated version could (1) vary continuously depending on the origin or destination and (2) vary depending on the combination of time period.

As a proxy for this taste for migration, I use the presence of a stock of migrants from the same origin state at the destination municipality in 1960. Section 3.5 gives more details about this variable. Note that I use the presence of a stock of all internal migrants, not simply working age men. The reason is that I want to measure the effect of time-invariant factors that would drive migration along a particular corridor and affect all potential migrants equally.

The reason I use the stock of migrants in 1960 is practical as well as historical. The earliest available Mexican census is in 1960. In addition, 1960 comes before the end of the Bracero program and the beginning of the export manufacturing program that we described in section 3.1. If these social networks represent long-run processes, using 1960 stocks as a control allows us to account for the unobservable initial conditions that started these processes and separate their effect from the effect of interest, the ongoing role of social networks in keeping migrant corridors open and inducing migration flow through these corridors. In the next section, we will present estimates of our model with and without this control. To my knowledge, this paper is the first one to model a taste for migration in this way.

4.4 Inference

In addition to identification issues that could bias the estimation of the effect of social networks, inference issues could interfere with the estimation of the significance of these effects. In particular, within-state correlation of unobservable factors related to migration destinations could affect the estimation of the significance of the effects of social networks on migration to these destinations. These factors include state-level policy decisions or industry-specific economic factors that could affect the labor demand and thus the migration flow across a particular state, for example. To address these inference issues, I cluster the standard errors by destination state using the standard cluster-robust variance-covariance matrix estimator.

5 Results and Discussion

In this section I will present the three main results of the empirical analysis, which estimates the extensive and intensive margin of internal migration separately. First, a structural gravity model with social networks provides additional explanatory power over a standard structural gravity model and a Roy-Borjas model with only differences in base wage and skill premium in estimating both margins across three time periods. Second, the effect of social networks monotonically increases at both margins across all three time periods; the effect of the other factors varies according to the migration climate. Third, the results hold up under a robustness check: a time-invariant migration taste factor.

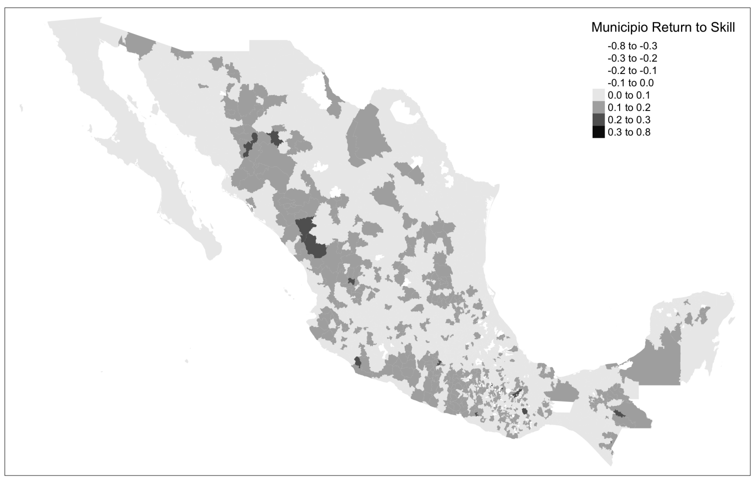

Figure 17: Return to Skill by Municipality (2010)

Table 5: Internal Migration in Period 2000-2005

	Dependent variable:		
	Internal Migrant Flow Present		
	(1)	(2)	(3)
Base Salary Diff	0.063*** (0.011)	0.013** (0.006)	0.006** (0.003)
Return to Skill Diff	0.859*** (0.155)	0.081 (0.061)	0.039 (0.035)
Distance (log)		−0.124*** (0.009)	−0.055*** (0.006)
Dest Population (log)		0.106*** (0.016)	0.055*** (0.010)
Origin on Border		0.052*** (0.015)	0.036*** (0.011)
Dest on Border		0.231*** (0.047)	0.085*** (0.029)
Origin Urban Share		0.237*** (0.026)	0.101*** (0.013)
Dest Urban Share		0.078*** (0.019)	0.045*** (0.012)
Origin Indig Share		0.073* (0.039)	0.024 (0.022)
Dest Indig Share		0.058*** (0.019)	0.029*** (0.010)
Social Network (log)			0.119*** (0.005)
Constant	0.196*** (0.021)	0.570*** (0.129)	0.202*** (0.070)
Observations	61,318	61,318	61,318
R^2	0.025	0.262	0.393
Adjusted R^2	0.025	0.262	0.393
Residual Std. Error	0.366 (df = 61315)	0.318 (df = 61307)	0.288 (df = 61306)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by destination state

Table 6: Internal Migration in Period 2000-2005

	Dependent variable:		
	Internal Migrant Flow (log)		
	(1)	(2)	(3)
Base Salary Diff	0.374*** (0.052)	0.079** (0.035)	0.022 (0.018)
Return to Skill Diff	4.355*** (0.903)	0.173 (0.449)	−0.359 (0.221)
Distance (log)		−0.396*** (0.038)	−0.103*** (0.026)
Dest Population (log)		0.463*** (0.039)	0.229*** (0.021)
Origin on Border		0.143** (0.066)	0.110*** (0.040)
Dest on Border		0.785*** (0.186)	0.324*** (0.107)
Origin Urban Share		0.927*** (0.155)	0.196** (0.092)
Dest Urban Share		0.137 (0.096)	0.027 (0.074)
Origin Indig Share		0.631*** (0.210)	0.175 (0.145)
Dest Indig Share		0.462*** (0.141)	0.295*** (0.076)
Social Network (log)			0.304*** (0.017)
Constant	3.278*** (0.060)	2.391*** (0.389)	1.068*** (0.296)
Observations	10,052	10,052	10,052
R^2	0.051	0.392	0.582
Adjusted R^2	0.051	0.391	0.581
Residual Std. Error	1.128 (df = 10049)	0.903 (df = 10041)	0.749 (df = 10040)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by destination state

5.1 Internal Migration at the Extensive Margin

Recall that table 4 provides a summary of the extensive margin across time: the presence of migration corridors. The models I present here estimate the factors that cause a corridor to open from one time period to the next or the factors that cause a corridor to stay open. For simplicity I will examine the extensive margin in one of the three time periods, but the analysis applies as well to the other two time periods. I choose the 2000-2005 time period because of better data availability at the start of the period in 2000.

Tables 5 and 5 shows three specifications of the extensive and intensive margins of migration to a destination municipality in the time period (2000-2005). Since I use a linear probability model for the extensive margin, I can directly interpret the coefficients as percentage increases in the probability of a migrant flow.

5.1.1 Specification 1: Wage Differentials

In specification (1) with only wage differentials, a one point increase in the base salary gap is associated with an 6.3% increase in the probability of a flow. An 0.1 increase in the return to skill difference is associated with a 8.6% increase in the probability of a flow. Because the dependent variables are calculated as coefficient differences from Mincer regressions, it is difficult to interpret these magnitudes directly. The sign and relative increase match the predictions of models that rely on wage differentials, however. Figures 13 and 16 show the base salary and return to skill by municipality for 2000.

The relatively low R^2 value of 0.025 indicates the poor predictive power of this model.

5.1.2 Specification 2: Structural Gravity Factors

Specification (2) adds other structural gravity factors: distance, destination population, presence on the border for origin and destination; urban share for origin and destination; and indigenous share for origin and destination. I discuss the impact of these factors in turn.

First, large cities drive migration; a one percent increase in destination population increases the probability of a migrant flow by 10%. Distance works against migration by increasing migration cost. Increasing the distance by a factor of 2.7 decreases the probability of a migrant flow by 12%.

An origin on the border could indicate an individual who has already migrated once or who has been deported. These individuals are predisposed to migration. It increases the probability of migration by 8%. A destination on the border increases the probability of migration by 23%. These municipalities attract migrants, either because of better jobs or the possibility of subsequent migration to the United States.

In this time period, the presence of a higher share of indigenous at both the origin and destination is associated with migration At the origin, the indigenous are likely to live in communities where there are little other economic opportunities than subsistence agriculture. At the destination: the indigenous, more than other groups, migrate where other indigenous are present. Figure 9 seems to confirm this trend. Visually it suggests that indigenous are migrating from their traditional communities in southern Mexico to work in the tourism industry around Cancun on the Yucatan Peninsula. An increase in 10% of the share at the origin increases the likelihood of a migrant corridor by 0.7%; an increase in 10% of the share at the destination increases the likelihood of a migrant corridor by 0.6%.

In this model, the wage difference factors do not matter as much. The impact of a one point base salary difference drops to 1.3% and remains significant. The impact of the return to skill difference loses significance. I can hypothesize that large, urban cities, especially on the border, offer the sort of labor markets that would have higher base salaries and reward education. Thus the structural gravity factors absorb the impact of the differences in labor models.

Overall, specification 2 has much more predictive power than specification 1, with an R^2 of 0.262.

5.1.3 Specification 3: Social Networks

The third specification reveals the core result of this paper. Here I augment the previous specification with the logged size of the social network, the migrant stock from the given origin state in the destination municipality at the beginning of the time period.

An increase of one log point in the size of the social network increases the probability of a migrant flow by 12%. Overall, specification 3 has even more predictive power than specification 2, with an $R^2 of 0.393$.

When I compare specification 3 to specification 2, the impact of the other factors in the model decreases by half: a one point impact in base salary, the presence of the origin or destination on the border, or the impact of the urban share at the origin or destination. These factors remain significant.

In the case of indigenous share, the impact at the origin loses significance, while the impact at the destination decreases by half. This result suggests that social networks especially play a role in the migration of the indigenous.

5.2 Internal Migration at the Intensive Margin

Next I use the same three specifications to analyze migration at the intensive margin: the magnitude of the internal migrant flow for the subset of possible migration corridors which are activated in a given time period.

Specifications (1) and (2) function in the same way their counterparts in specifications (1) and (2) in the extensive margin case. Initially, differences in the base salary and return to skill seem to drive migration but the introduction of structural gravity factors dramatically reduces the explanatory power of these factors. The same structural factors that drove the presence of a migrant flow also drive the magnitude of the flow.

Examining the role of social networks in specification (3) confirms the core result of this paper. In this log-log model, I can interpret this coefficient as a social network elasticity. An increase in 1% of the size of the social network in one time period causes an increase in 0.3% of the magnitude of the migrant flow in the subsequent time period. The addition of social networks to the model decreases the magnitude of the effects of other factors by half or more. In particular, it eliminates the effect of indigenous share at the origin or urban share at the destination, suggesting the size of the social network accounts for the variation previously explained by these factors. The predictive power of this model is quite high at 0.582.

5.3 Migration Climate

For the potential migrant, internal migration and international migration are related. In practice, the decision to internally migrate takes into consideration both the expected value of staying as well as the expected value of international migration. An extension of this model would incorporate all three options—staying, internal migration, and internal migration—into one integrated model.

For the three periods in question, I note certain contextual factors through which the outside option of US-Mexico migration varies in the three periods that we study. Villarreal (2014) and Durand and Massey (2019) provide more background on these trends.

1. From 1995-2000, migration from Mexico to the US was increasing, owing to the recent passage of NAFTA and a relatively porous border.

2. From 2000-2005, border security increased as a result of the September 11 attacks. The Mexican economy continued to recover from the 1994

"tequila crisis" and associated devaluation of the peso.

3. From 2010-2015, the global economic recession of 2008 caused the return of an estimated 500,000 temporary migrants from the US to Mexico. US-Mexico migration peaked and begun to decline.

Examining the determinants of internal migration in these three time periods will allow us to indirectly examine the overall "migration climate" of individuals and the relative ease or difficulty of these outside options.

In addition to the value of the outside option, changing conditions in the Mexican economy have also affected internal migration. As part of an overall shift in Mexico's economy from rural agriculture to urban industry, the labor market of the rural agricultural sector has changed. Residents of rural areas have sorted into productive farmers, who continue to make a profit despite challenging market environments, and non-productive farmers, who have abandoned subsistence farming in search of other opportunities. These other opportunities include local non-agricultural work and migration within Mexico in addition to international migration (Charlton & Taylor, 2016). Our use of migration flows from Mexican population census data complements the household-level migration histories from the National Rural Mexican Household Survey panel that these authors use. We do not examine international migration flows from the origin states directly. Nevertheless, the changes we observe in the determinants of migration over the three time periods of interest match these authors' conclusions about the increasing availability of high-skilled non-farm job opportunities in Mexico.

Table 7: Extensive Margin of Internal Migration Across Time

	Dependent variable:		
	Internal Migrant Flow Present		
	1995-2000	2000-2005	2010-2015
	(1)	(2)	(3)
Base Salary Diff	0.006* (0.004)	0.006** (0.003)	0.012*** (0.003)
Return to Skill Diff	−0.084 (0.088)	0.039 (0.035)	0.153** (0.065)
Distance (log)	−0.170*** (0.008)	−0.055*** (0.006)	−0.110*** (0.009)
Dest Population (log)	0.114*** (0.009)	0.055*** (0.010)	0.034*** (0.005)
Origin on Border	0.082*** (0.015)	0.036*** (0.011)	0.057*** (0.016)
Dest on Border	0.215*** (0.044)	0.085*** (0.029)	0.052 (0.036)
Origin Urban Share	0.126*** (0.041)	0.101*** (0.013)	0.151*** (0.044)
Dest Urban Share	0.162*** (0.025)	0.045*** (0.012)	0.057*** (0.009)
Origin Indig Share		0.024 (0.022)	−0.003 (0.028)
Dest Indig Share		0.029*** (0.010)	−0.005 (0.008)
Social Network (log)	0.046*** (0.005)	0.119*** (0.005)	0.126*** (0.009)
Constant	1.197*** (0.095)	0.202*** (0.070)	1.180*** (0.101)
Observations	19,437	61,318	71,579
R^2	0.323	0.393	0.324
Adjusted R^2	0.323	0.393	0.324
Residual Std. Error	0.391 (df = 19427)	0.288 (df = 61306)	0.352 (df = 71567)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by destination state

Table 8: Intensive Margin of Internal Migration Across Time

	Dependent variable:		
	Internal Migrant Flow (log)		
	1995-2000	2000-2005	2010-2015
	(1)	(2)	(3)
Base Salary Diff	0.039*** (0.004)	0.022*** (0.003)	0.087*** (0.003)
Return to Skill Diff	−0.059 (0.088)	−0.359*** (0.035)	0.619*** (0.065)
Distance (log)	−0.481*** (0.008)	−0.103*** (0.006)	−0.193*** (0.009)
Dest Population (log)	0.609*** (0.009)	0.229*** (0.010)	0.437*** (0.005)
Origin on Border	0.017 (0.015)	0.110*** (0.011)	0.056*** (0.016)
Dest on Border	0.832*** (0.044)	0.324*** (0.029)	0.142*** (0.036)
Origin Urban Share	0.707*** (0.041)	0.196*** (0.013)	0.338*** (0.044)
Dest Urban Share	0.476*** (0.025)	0.027** (0.012)	0.138*** (0.009)
Origin Indig Share		0.175*** (0.022)	0.052* (0.028)
Dest Indig Share		0.295*** (0.010)	−0.091*** (0.008)
Social Network (log)	0.190*** (0.005)	0.304*** (0.005)	0.319*** (0.009)
Constant	1.605*** (0.095)	1.068*** (0.070)	−0.375*** (0.101)
Observations	6,654	10,052	17,307
R^2	0.536	0.582	0.675
Adjusted R^2	0.535	0.581	0.675
Residual Std. Error	1.119 (df = 6644)	0.749 (df = 10040)	0.835 (df = 17295)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by destination state

5.4 Social Networks Across Time

Next I use our structural gravity and social networks model across the three time periods of interest at the extensive and intensive margin. I present the results in Table 5.3 and 5.3.

The effect of the social network is monotonically increasing across time periods. A one log point increase in the size of the social network causes a 4.1%, 11.6%, or 12.7% increase in the probability of a migrant flow, respectively. Conditional on the presence of a migrant flow, a 1% increase in the size of the network increases the flow by 17.3%, 28.6%, or 30.6%.

Changes in the effect and significance of the other factors in the model reflect changing economic conditions in Mexico.

Base salary difference matters slightly in all three time periods, while return to skill only matters in the third time period. This result matches other literature like Charlton and Taylor (2016) which suggests that Mexico is in the late stages of a structural transition where education and non-farm opportunities have increased together.

Distance matters less over time. I imagine the increasing presence of communications technology like cell phones and the Internet as well as the ease of travel within Mexico reducing the effect of physical and psychic costs that distance models.

I see urban-urban migration across all three time periods at both margins. The presence of this migration instead of purely rural-urban migration contributes to the evidence for a structural transformation in Mexico.

In contrast, the effect of a destination on the border drops across three time periods. This result matches US-Mexico migration trends, which peaked in 2007. It suggests decreasing transit migration from the first to the second time period and an absence of this type of migration in the third time period.

In the two time periods for which I have data, indigenous migration above and beyond general trends plays a role in the first but not the second. In 2005, the indigenous tended to migrate where other indigenous were present, but not in 2015 ten years later.

Table 9: Extensive Margin of Internal Migration Across Time

	Dependent variable:		
	Internal Migrant Flow Present		
	1995-2000	2000-2005	2010-2015
	(1)	(2)	(3)
Base Salary Diff	0.006 (0.015)	0.006 (0.018)	0.012 (0.041)
Return to Skill Diff	−0.084 (0.299)	0.044 (0.221)	0.152 (0.478)
Distance (log)	−0.163*** (0.029)	−0.055** (0.026)	−0.110*** (0.024)
Dest Population (log)	0.105*** (0.026)	0.053*** (0.021)	0.034 (0.029)
Origin on Border	0.077 (0.062)	0.035 (0.040)	0.057 (0.039)
Dest on Border	0.190 (0.158)	0.077 (0.107)	0.053 (0.101)
Origin Urban Share	0.134 (0.198)	0.105 (0.092)	0.151 (0.114)
Dest Urban Share	0.159 (0.119)	0.045 (0.074)	0.057 (0.040)
Origin Indig Share		0.027 (0.145)	−0.003 (0.095)
Dest Indig Share		0.028 (0.076)	−0.005 (0.066)
Social Network (log)	0.041*** (0.012)	0.116*** (0.017)	0.127*** (0.013)
Stock Present in 1960	0.141	0.073	−0.008
Constant	1.183*** (0.388)	0.207 (0.296)	1.180*** (0.227)
Observations	19,437	61,318	71,579
R^2	0.328	0.395	0.324
Adjusted R^2	0.328	0.394	0.324
Residual Std. Error	0.389 (df = 19426)	0.288 (df = 61305)	0.352 (df = 71566)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by destination state

Table 10: Intensive Margin of Internal Migration Across Time

	Dependent variable:		
	Internal Migrant Flow (log)		
	1995-2000	2000-2005	2010-2015
	(1)	(2)	(3)
Base Salary Diff	0.036** (0.015)	0.027 (0.018)	0.094** (0.041)
Return to Skill Diff	−0.087 (0.299)	−0.197 (0.221)	0.766 (0.478)
Distance (log)	−0.411*** (0.029)	−0.082*** (0.026)	−0.182*** (0.024)
Dest Population (log)	0.535*** (0.026)	0.200*** (0.021)	0.421*** (0.029)
Origin on Border	−0.033 (0.062)	0.086** (0.040)	0.052 (0.039)
Dest on Border	0.690*** (0.158)	0.255** (0.107)	0.072 (0.101)
Origin Urban Share	0.768*** (0.198)	0.265*** (0.092)	0.384*** (0.114)
Dest Urban Share	0.463*** (0.119)	0.030 (0.074)	0.139*** (0.040)
Origin Indig Share		0.260* (0.145)	0.102 (0.095)
Dest Indig Share		0.285*** (0.076)	−0.085 (0.066)
Social Network (log)	0.175*** (0.012)	0.286*** (0.017)	0.306*** (0.013)
Stock Present in 1960	0.613	0.388	0.324
Constant	1.391*** (0.388)	1.052*** (0.296)	−0.405* (0.227)
Observations	6,654	10,052	17,307
R^2	0.554	0.594	0.679
Adjusted R^2	0.553	0.593	0.678
Residual Std. Error	1.097 (df = 6643)	0.738 (df = 10039)	0.830 (df = 17294)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by destination state

5.5 Migration Taste Factor

As I mention in the section 4.3 one threat to the identification of the effect of social networks is the presence of serial correlation: some unobserved factor that affects a migration flow in one period and in the next.

I use a simple model of such a factor that we call a taste for a particular migration corridor. Tables 5.4 and 5.4 show revised estimations with the inclusion of this taste factor. It is significant across 5 of the 6 estimated equations, which indicates the role of taste in migration. On the other hand, it does not change appreciably the magnitude, sign, or significance of our results at the extensive margin. At the intensive margin, it brings down the magnitude of the social network coefficient by approximately 10%. These results suggest that the effects of social networks that I have estimated are not caused by a mere taste for certain migration corridors. Further work could examine the role of this taste for migration in the initial conditions that jumpstarted these social networks.

6 Conclusion

This paper has used a structural gravity model to estimate the effect of social networks on the extensive margins and intensive margins of migrant flows from origin states to destination municipalities in Mexico over the time periods 1995-2000, 2000-2005, and 2010-2015. The extensive margin refers to the presence of a migration corridor; the intensive margin refers to the magnitude of migrant flow through this corridor. It uses a sample of working age men from 25-55 who would most likely migrate for economic instead of non-economic reasons to compare the explanatory power of a Roy model, a structural gravity model without social networks, and a structural gravity model with social networks. In the third model, it aims to identify the effect of the social networks.

I find two main results.

First, in all three time periods, the model reveals a rich set of factors other than wage differences and return to skill that are associated with the presence of migration corridors and the magnitude of migrant flow through them. These factors include urbanization share, indigenous share, and presence on the US/Mexico border. I am interested in particular in identifying the effect of the presence and size of a social network of migrants from the same origin state who migrated in the previous time period. To identify this effect, I use the presence of a migrant flow from 1960 along the same corridor to control for serially-correlated unobservables that could influence the size of the social network across time periods. I call this control a "taste for migration" along a particular corridor.

In a representative time period (2000-2005), a model that includes only differences in base salary and return to skill explains 2.5% of the variation in the presence of migration corridors; additional structural gravity factors 26%; and the social network 39% The corresponding models of the magnitude of the migrant flow explain 5%, 39%, and 58% of the variation, respectively.

Thus social networks add explanatory power to structural gravity models at the extensive and intensive margins. Both models vastly outperform standard Roy migration models that focus only on individual utility maximization.

Moreover, across all three time periods, the effect of social networks is monotonically increasing. At the extensive margin, a 1% increase in the size of the social network increases by 5%, 12%, and 13% the likelihood of a migration corridor. At the intensive margin, the equivalent social network elasticities are 19%, 30%, and 32%.

Estimating these models separately for each time period reveals changes in the Mexican economy that affect internal migration: including increased educational opportunities and the decreasing appeal of migration to the US.

These results contribute to a strand of literature in the economics of migration that argues not only for the importance of considering social networks or diaspora effects but that these effects dominate economic effects as drivers of migration. Moreover, they do so in a novel context of internal migration instead of international migration.

One novelty of our approach, the use of Mexican census data, is also its limitation. Since we use the nationally representative Mexican census collected every five years instead of smaller scale panel data surveys that ask for more detailed migration histories, we can only account for long-term permanent migration that occurs at most one time per time period. Moreover, we consider here the weak ties of migrants from the same state instead of using a more granular measure of migrants from the same municipality.

Moreover, though we restrict the sample to men aged 25-55 who would tend to migrate for work, we still observe that many of the individuals in this sample migrate for reasons other than employment. Other data sources, such as the quarterly Mexican Survey of Occupation and Employment (ENOE), would provide a targeted look at internal migrants who obtain formal employment at a much higher temporal frequency. These data sources would provide the ability to understand more deeply the mechanism by which new migrants help existing migrants find jobs.

Finally, further research in the origin of migrant networks in specific contexts such as Mexico is needed to provide a better understanding for what causes corridors to develop in the first place. Ideally, this research would reveal an instrument that could be used to credibly identify the effect of these social networks.

Nevertheless, the results here provide useful tools for several sets of actors as they seek to predict and respond to internal migration trends: local and state governments in receiving communities that must accommodate new populations; export manufacturing factories and other sources of employment for new migrants; and NGOs that facilitate their integration into receiving communities.

References

Anderson, J. E. (2011). The gravity model [Publisher: Annual Reviews]. *Annual Review of Economics*, *3*(1), 133–160. https://doi.org/10.1146/annurev-economics-111809-125114

Arends-Kuenning, M., Baylis, K., & Garduño-Rivera, R. (2019). The effect of NAFTA on internal migration in mexico: A regional economic analysis [Publisher: Routledge _eprint: https://doi.org/10.1080/00036846.2018.1524976]. *Applied Economics*, *51*(10), 1052–1068. https://doi.org/10.1080/00036846.2018.1524976

Asad, A. L., & Garip, F. (2019). Mexico-u.s. migration in time: From economic to social mechanisms [Publisher: SAGE Publications Inc]. *The ANNALS of the American Academy of Political and Social Science*, *684*(1), 60–84. https://doi.org/10.1177/0002716219847148

Banerjee, B. (1991). The determinants of migrating with a pre-arranged job and of the initial duration of urban unemployment: An analysis based on indian data on rural-to-urban migrants. *Journal of Development Economics*, *36*(2), 337–351. https://doi.org/10.1016/0304-3878(91)90040-3

Beine, M., Bertoli, S., & Fernández-Huertas Moraga, J. (2016). A practitioners' guide to gravity models of international migration [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/twec.12265]. *The World Economy*, *39*(4), 496–512. https://doi.org/10.1111/twec.12265

Beine, M., Docquier, F., & Özden, Ç. (2011). Diasporas. *Journal of Development Economics*, *95*(1), 30–41. https://doi.org/10.1016/j.jdeveco.2009.11.004

Borjas, G. J. (1987). Self-selection and the earnings of immigrants [Publisher: American Economic Association]. *The American Economic Review*, *77*(4), 531–553. Retrieved March 8, 2022, from http://www.jstor.org/stable/1814529

Carrington, W. J., Detragiache, E., & Vishwanath, T. (1996). Migration with endogenous moving costs [Publisher: American Economic Association]. *The American Economic Review*, *86*(4), 909–930. Retrieved May 8, 2022, from http://www.jstor.org/stable/2118311

Charlton, D., & Taylor, J. E. (2016). A declining farm workforce: Analysis of panel data from rural mexico [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1093/ajae/ *American Journal of Agricultural Economics*, *98*(4), 1158–1180. https://doi.org/10.1093/ajae/aaw018

Chiquiar, D. (2005). Why mexico's regional income convergence broke down. *Journal of Development Economics*, *77*(1), 257–275. https://doi.org/10.1016/j.jdeveco.2004.03.009

Chiquiar, D., & Hanson, G. H. (2005). International migration, self-selection, and the distribution of wages: Evidence from mexico and the united states [Publisher: The University of Chicago Press]. *Journal of Political Economy*, *113*(2), 239–281. https://doi.org/10.1086/427464

Cuecuecha, A., & Pederzini, C. (2014). *Migration and remittances from mexico: Trends, impacts, and new challenges* [OCLC: 994041414].

Davis, B., Stecklov, G., & Winters, P. (2002). Domestic and international migration from rural mexico: Disaggregating the effects of network structure and composition [Publisher: [Population Investigation Committee, Taylor & Francis, Ltd.]]. *Population Studies*, *56*(3), 291–309. Retrieved May 8, 2022, from http://www.jstor.org/stable/3092983

Durand, J., & Massey, D. S. (2019). Evolution of the mexico-u.s. migration system: Insights from the mexican migration project [Publisher: SAGE Publications Inc]. *The ANNALS of the American Academy of Political and Social Science*, *684*(1), 21–42. https://doi.org/10.1177/0002716219857667

Falaris, E. M. (1987). A nested logit migration model with selectivity [Publisher: [Economics Department of the University of Pennsylvania, Wiley, Institute of Social and Economic Research, Osaka University]]. *International Economic Review*, *28*(2), 429–443. https://doi.org/10.2307/2526735

Garip, F., & Asad, A. L. (2016). Network effects in mexico–u.s. migration: Disentangling the underlying social mechanisms [Publisher: SAGE Publications Inc]. *American Behavioral Scientist*, *60*(10), 1168–1193. https://doi.org/10.1177/0002764216643131

Granovetter, M. S. (1973). The strength of weak ties [Publisher: University of Chicago Press]. *American Journal of Sociology*, *78*(6), 1360–1380. Retrieved March 20, 2022, from http://www.jstor.org/stable/2776392

Hanson, G. H. (2001). U.s.–mexico integration and regional economies: Evidence from border-city pairs. *Journal of Urban Economics*, *50*(2), 259–287. https://doi.org/10.1006/juec.2001.2217

Harris, J. R., & Todaro, M. P. (1970). Migration, unemployment and development: A two-sector analysis [Publisher: American Economic Association]. *The American Economic Review*, *60*(1), 126–142. Retrieved March 8, 2022, from http://www.jstor.org/stable/1807860

Ibarraran, P., & Lubotsky, D. (2007). Mexican immigration and self-selection: New evidence from the 2000 mexican census. *Mexican immigration to the United States*, 159–192.

Integrated public use microdata series, international: Version 7.3 [dataset]. minneapolis, MN: IPUMS, 2020. [Type: Dataset]. (2020). https://doi.org/https://doi.org/10.18128/D020.V7.3

Lucas, R. E. B. (2021, November 18). *Crossing the divide: Rural to urban migration in developing countries*. https://doi.org/10.1093/oso/9780197602157.001.0001

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem [Publisher: [Oxford University Press, Review of Economic Studies, Ltd.]]. *The Review of Economic Studies*, *60*(3), 531–542. https://doi.org/10.2307/2298123

Marek Hlavac. (2022). *Stargazer: Well-formatted regression and summary statistics tables* (Version 5.2.3). Bratislava, Slovakia, Social Policy Institute. https://CRAN.R-project.org/package=stargazer

Martin, P. (2020, July 10). *Mexican braceros and US farm workers* [Wilson center]. Retrieved May 8, 2022, from https://www.wilsoncenter.org/article/mexican-braceros-and-us-farm-workers

McKenzie, D., & Rapoport, H. (2010). SELF-SELECTION PATTERNS IN MEXICO-u.s. MIGRATION: THE ROLE OF MIGRATION NETWORKS [Publisher: The MIT Press]. *The Review of Economics and Statistics*, *92*(4), 811–821. Retrieved May 8, 2022, from http://www.jstor.org/stable/40985796

Miles, C. H., Petersen, M., & van der Laan, M. J. (2019). Causal inference when counterfactuals depend on the proportion of all subjects exposed. *Biometrics*, *75*(3), 768–777. https://doi.org/10.1111/biom.13034

Morgan, S. L., & Winship, C. (2014, November 17). *Counterfactuals and causal inference: Methods and principles for social research* (2nd edition). Cambridge University Press.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the u. s. labor market*. *The Quarterly Journal of Economics*, *118*(2), 549–599. https://doi.org/10.1162/003355303321675455

Munshi, K. (2020). Social networks and migration [Publisher: Annual Reviews]. *Annual Review of Economics*, *12*(1), 503–524. https://doi.org/10.1146/annurev-economics-082019-031419

Ochoa, L. C. M., Ponce, R. A. C., & Espinosa, M. d. L. R. (2018). Migración interna en México. *Paradigma económico. Revista de economía regional y sectorial*, *10*(2), 39–59. Retrieved March 19, 2022, from https://www.redalyc.org/journal/4315/431564589002/html/

Ramos, R. (2016). Gravity models: A tool for migration analysis. *IZA World of Labor*. https://doi.org/10.15185/izawol.239

Roy, A. D. (1951). Some thoughts on the distribution of earnings [Publisher: Oxford University Press]. *Oxford Economic Papers*, *3*(2), 135–146. Retrieved March 8, 2022, from http://www.jstor.org/stable/2662082

Silva, J. M. C. S., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, *88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Sjaastad, L. A. (1962). The costs and returns of human migration [Publisher: University of Chicago Press]. *Journal of Political Economy*, *70*(5), 80–93. Retrieved March 8, 2022, from http://www.jstor.org/stable/1829105

Soloaga, Isidro, Lara Ibarra, Gabriel, & Wendelspiess, Florian. (2010). Determinantes de la migración interestatal: 1995-2000 y 2000-2005. In N. Lustig, Yunez, Antonio, & Sabido, Alfonso Castañeda (Eds.), *Economía rural* (pp. 172–194). El Colegio de México.

Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What are we weighting for? [Publisher: University of Wisconsin Press]. *Journal of Human Resources*, *50*(2), 301–316. https://doi.org/10.3368/jhr.50.2.301

UNESCO. (2018, October 29). *Internal migration — 2019 GEM report*. Retrieved May 2, 2022, from http://gem-report-2019.unesco.org/chapter/introduction/internal-migration/

Villarreal, A. (2014). Explaining the decline in mexico-u.s. migration: The effect of the great recession. *Demography*, *51*(6), 2203–2228. https://doi.org/10.1007/s13524-014-0351-4

Woodruff, C., & Zenteno, R. (2007). Migration networks and microenterprises in mexico. *Journal of Development Economics*, *82*(2), 509–528. https://EconPapers.repec.org/RePEc:eee:deveco:v:82:y:2007:i:2:p:509-528

Yap, L. Y. L. (1977). The attraction of cities: A review of the migration literature. *Journal of Development Economics*, *4*(3), 239–264. https://doi.org/10.1016/0304-3878(77)90030-X