Herd Effects or Migration Networks? The Location Choice of Mexican Immigrants in the U.S.*

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July 17, 2002

ABSTRACT

This paper addresses the question: Why and where do immigrants cluster? We examine the relative importance and interaction of two alternative explanations of immigrant clustering: (1) network externalities and (2) herd behavior. We advance the theory by presenting a framework encompassing both network and herd effects, and by delineating various types of network and herd effects in our empirical work. In order to distinguish between herd and network externalities, we use the Mexican Migration Project data. Our empirical results show that both network externalities and herds have significant effects on the migrant's decision of where to migrate. Moreover, the significance and size of the effects vary according to the legal status of the migrant and whether the migrant is a "new" or a "repeat" migrant. The network-externality effect has an inverse U shape, not simply a linear positive effect as often presented in the literature. Neglecting herds and/or networks, or the inverse U shape of network effects leads to faulty conclusions about migrant behavior.

Keywords: Herd effects, networks, immigration, location choice
JEL classification: F22, J61
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*We thank Julie Phillips for discussions and helping us with the data. We thank David Jaeger, John Landon-Lane and Myeong-Su Yun for their comments. We also thank Barry Chiswick for asking the right question at the right time. This paper was partly written while Gil Epstein and Ira Gang were visiting IZA, Bonn. Ira Gang thanks the Rutgers Research Council for partial support. Earlier versions of this paper were presented at the NEUDC Conference, Ithaca, NY and at the IZA Transatlantic Labor Economics Workshop, Ammersee, Germany.

1. INTRODUCTION

A striking characteristic of international migration is the clustering of immigrants in ethnic communities. Among others, prominent examples of the clustering of migrants are the concentrations of Turks in Germany, Tamils in Switzerland, Moroccans in the Netherlands and Belgium, Italians in Argentina, Greeks in Australia, and Ukrainians in Canada. While clustering can reflect language proficiency due to former colonial relations, often knowledge of the host language is not a characteristic of the clustered immigrants. Clustering can be very narrow, such as when immigrants from a town or region are concentrated in a specific foreign town or region. For example, Macedonians from Skopje have come to make up a notable part of the population of Gothenburg, Sweden. In the United States, noticeable clusters of Mexican immigrants exist in California, Texas, Florida and Chicago. 58% of migrants from Guanajuato, the Mexican state with the highest emigration rate to the U.S., go to California and another 23% to Texas.

The prevailing explanation for immigrant clustering is the existence of beneficial network externalities. These externalities arise when previous immigrants provide shelter and work, assistance in obtaining credit, and/or generally reduce the stress of relocation to a foreign culture. Network externalities imply "I will go to where my people are, since it will help me." Thus, the stock of migrants in a certain location directly affects the utility a migrant will receive by joining the ethnic community. An alternative explanation for the clustering of immigrants in a specific location is "herd behavior." The argument of the herd behavior hypothesis is quite different from the hypothesis of network externalities. Herd behavior implies: "I will go to where I have observed others go, because all these others who went before most probably have information that I do not have, even though I would have chosen independently to go elsewhere." Herd behavior thus encourages migrants to discount private information. Following the hypothesis of herd behavior, emigrants will follow the flow of other migrants.

There is a substantial literature on network externalities in migration (see Gottlieb (1987), Grossman (1989), Marks (1989), Stark (1991), Church and King (1993), Carrington, Detragiache, and Vishwanath (1996), Chiswick and Miller (1996), Zahniser

(1999), and Munshi (2001)). Ethnic networks, however, might also be associated with negative externalities. Disadvantageous network externalities may arise if immigration is subject to adverse selection (high productivity immigrants do not want low-productive people to immigrate (Stark (1991), (1995)), or if increases in the number of foreigners increase competition for jobs and lower immigrants' wages. Negative network externalities limit the number of immigrants who can benefit from network externalities. Bauer and Gang (1999) have examined network effects in a model of return migration.

Several empirical studies investigate the determinants of the location choice of immigrants in the United States. Bartel (1989) finds that post-1964 U.S. immigrants tend to locate in cities with a high concentration of immigrants of similar ethnicity. She further shows that more highly skilled migrants are less geographically concentrated and rely less on the location of fellow countrymen. Dunlevy (1991), focusing on Caribbean and Latin immigrants to the U.S., and Jaeger (2000), who differentiates between immigrants of different admission status, find that immigrants tend to locate where former immigrants of the same ethnicity are concentrated.

Although a number of studies have underscored the importance of networks in migration, the argument that immigrant clustering could be explained by herd behavior has only recently been introduced to the migration literature. Following Epstein (2002), potential migrants may have some private information but are imperfectly informed about the attributes of alternative foreign locations. Potential migrants, however, observe previous emigrants' decisions, but not the information signal that was driving the decision of previous emigrants. Behavior is rational on the supposition by new emigrants that previous emigrants had information that they do not have. The outcome is that emigrants discount private information and duplicate a location that previous emigrants have been observed to choose. Thus, they are following the flow of immigrants. In engaging in such herd behavior, people may come to realize that they have made a mistake, and may be seen to change their minds about to where to locate. Herd behavior might result in inefficiencies, since it is possible that migrants would have received a higher utility if they had relied on their private information when making the location decision rather than following the herd.

Unlike network externalities, the information-based theory of herd behavior requires no prior concentration of one's own co-patriots in a foreign location. There is, however, no reason why network externalities should not coexist with the information structure that underlies herd behavior. Beneficial network externalities may be available in the different alternative locations from which an immigrant can choose, and still information aspects can give rise to herd behavior. Since herd behavior and network externalities can clearly coexist, we account for the presence of both and consider their interaction.

This paper contributes to the existing literature on migrants' location decisions in two major respects. First, we examine the relative importance and interaction of two alternative explanations of immigrant clustering on a theoretical as well as empirical basis: (1) network externalities (stock of migrants) and (2) herd behavior (flow of migrants). Second, by using an extensive Mexican data set, we contribute to the existing literature on migration between Mexico and the US. In absolute numbers, the U.S. is the world's largest country of immigration; Mexico is the world's major country of emigration. Migration from Mexico to the United States is the largest sustained flow of migration in the world. Empirical evidence suggests that there exist strong network effects in Mexican migration (Bustamante (1998), Munshi (2001), and Winters, de Janvry and Sadoulet (2001)).

In the next section we develop the theory of herd effects and migration networks. We describe our data, and define and characterize the variables we employ in Section 3. Section 4 presents our statistical analysis, while Section 5 offers some concluding comments.

2. THE THEORY OF HERD EFFECTS AND MIGRATION NETWORKS

Based on Epstein (2002), this section provides a theoretical framework for the analysis of the relative importance and interaction of herd behavior and network externalities in determining migration behavior. Both of these motivations give rise to immigrant clustering, a phenomenon observed in a wide variety of migration destinations.

Among different alternative foreign locations for immigration, one location objectively offers better conditions than others. The framework that is the basis for herd behavior assumes that the identity of this best foreign location is unknown to potential migrants. They have a uniform prior over foreign locations. Emigrants have some private information but are imperfectly informed about the attributes of alternative foreign locations. They further observe previous emigrants' decisions. Emigration decisions are made sequentially, with people contemplating emigration at a given age or stage in their lives. In the sequential decision process, people at different stages make decisions regarding emigration at different times. An individual may receive a signal about the quality of a particular foreign region and can observe the behavior of previous migrants. Potential emigrants cannot, however, observe the information signal that was the basis for previous migrants' decisions. Given the information available, each individual chooses a country to which to immigrate.

Network externalities include the role of social and informational networks. Ties of kinship, friendship, and village, link migrants, former migrants, and non-migrants in the home and host country. In an uncertain environment, migration networks provide information about the labor market in the host country and thus may increase the expected wage and decrease uncertainty by enabling the migrant to obtain better-paid and more stable jobs.

Based on the hypothesis of positive network externalities, relocation costs decrease with the stock of immigrants, which encourages more emigration, and leads to immigrant clustering -- but some immigrant clustering must already have been present to provide the externalities. Herd behavior, which addresses information issues, can be under way before migrants reduce the moving costs of others.

2.1. Network Behavior

Consider individual *j's* utility from migrating to a certain country, $U_j\,(.)$, which is a function of two variables: the wage that the migrant will receive by migrating to the new location, w_j, and the stock of immigrants from the same origin who previously migrated to the new location, N. From the above discussion, a migrant's utility increases with his wage and with network externalities, i.e. the stock of previous migrants. Thus,

$$\frac{\partial U_j(w_j, N)}{\partial w_j} > 0 \quad \textit{and} \quad \frac{\partial U_j(w_j, N)}{\partial N} > 0 \quad . \tag{1}$$

For a given utility level, an iso-utility locus (indifference curve) is described by:

$$d U_j(w_j, N) = \frac{\partial U_j(w_j, N)}{\partial w_j} d w_j + \frac{\partial U_j(w_j, N)}{\partial N} d N = 0 . \tag{2}$$

Since there is a trade-off between the wage level in the host country and the stock of previous immigrants, the iso-utility locus is downward sloping, i.e.:

$$\frac{d w_j}{d N} = -\frac{\dfrac{\partial U_j(w_j, N)}{\partial N}}{\dfrac{\partial U_j(w_j, N)}{\partial w_j}} < 0 . \tag{3}$$

Moreover, as we increase the wage and the stock of previous migrants from the same origin, the utility of the new migrant increases.

Assume a normal downward sloping demand function for workers in the host country, $q^d(w_f)$, such that $\frac{\partial q^d(w_f)}{\partial w_f} < 0$, and an upward sloping supply function of workers $q^s(N_L, N)$, where N_L is the size of the local population such that $\frac{\partial q^s(N_L, N)}{\partial N} > 0$. In equilibrium $q^d(w_f) = q^s(N_L, N)$. Equilibrium wages are given by $w_f^*(N)$. Hence, the equilibrium wage is a function of the stock of immigrants in the country. It can be easily show that the equilibrium wage decreases with the stock of immigrants, i.e. $\frac{\partial w^*{}_f(N)}{\partial N} < 0$.[1] Of course, the wages of immigrants are also a function of the local population size. In the following, we assume that the local population size is constant.

Let us now consider the total effect of an increase in the stock of immigrants on the migrants' utility level. The full derivative of a change in the size of the stock of immigrants on the migrant's utility is given by:

$$\frac{dU_j\left(w_f^*, N\right)}{d\,N} = \frac{\partial U_j\left(w_f^*, N\right)}{\partial N} + \frac{\partial U_j\left(w_f^*, N\right)}{\partial w_f^*}\frac{\partial\ w_f^*}{\partial\ N} \tag{4}$$

Equation (4) shows that the stock of migrants (the network effect) affects utility in two ways: directly via positive externalities and indirectly via negative effects on the wage. The first component on the RHS of (4) is positive while the second component is negative. The "old" migrants (the stock of immigrants), who are already in the host country, prefer that the maximum number of migrants coming to this country will be such that (4) equals zero.[2] That is, the marginal increase in the migrants' utility from externalities equals the marginal effect of the decrease in wages resulting from an additional migrant:

$$\frac{\partial U_j\left(w_f^*, N\right)}{\partial N} = -\ \frac{\partial U_j\left(w_f^*, N\right)}{\partial w_f^*}\frac{\partial\ w_f^*}{\partial\ N} \quad . \tag{5}$$

Equations (4) and (5) together with the second order condition gives us the optimal stock of immigrants in the sense that this is the stock preferred by migrants already living in the host country. Denote this stock by N_1. For a migrant stock below N_1 an additional immigrant to the location increases the utility of the migrants already living in the

[1] See, for example, Gang and Rivera-Batiz (1994) as one of several articles that examine the relationship between immigrants and the wages of previous immigrants as well as the native-born.

[2] The second order condition must satisfy: $\frac{d^2U_j\left(w_f^*, N\right)}{d\,N^2} < 0$.

location, since the effect of the positive externalities is stronger than the decrease in wages. Beyond N_1, an additional immigrant will cause the utility of the migrants already present at the host country to decline, as the effect of the decrease in wages on the utility of previous migrants is stronger than the respective increase in network externalities. Hence, migrants who have already immigrated to the new country want the stock of immigrants not to exceed N_1. (See Figure 1)

A new migrant who is considering migrating to this host country takes into account the stock of immigrants already in the host country, N, *plus* the *expected* number of migrants who will decide to go to this host country after he has migrated, $E(N)$. The migrant compares his expected utility from going to this country with the expected utility from migrating to a different region.

As argued above, given that the immigrant is already in the host country, he prefers the stock of immigrants to equal N_1. However, when this individual makes his decision whether or not to migrate to this county, he compares the expected utility from different countries and chooses the one with the highest value. We therefore may see migrants deciding to migrate to a country in which the stock of migrants has already exceeded N_1. Thus, the probability that an individual chooses to migrate to a country where the stock of immigrants already exceeds N_1 is positive. This probability, however, decreases as the stock of immigrants already in the host country increases. We conclude,

Given network externalities, the probability an individual migrates to a certain country has an inverse U shape relationship with regard to the stock of immigrants already in the host country. (See Figure 2.)

2.2. Herd Behavior

Following Epstein (2002) migration decisions are made sequentially, with people contemplating emigration at a given stage in their lives. In herd behavior, individuals respond (or not) to signals or information packets about host country possibilities. An individual receives a signal with probability p. With probability q this signal is true. The individual further observes the behavior of previous migrants. Potential migrants cannot, however, observe the information signal that was the basis for previous migrants' decisions. Given the information available, each individual chooses a country to which to migrate. The structure of the game and Bayesian rationality are common knowledge.

Three assumptions govern individuals' actions (these assumptions *minimize the likelihood* of herd behavior): (a) an individual, who does not receive a signal and observes that everybody else has chosen to stay home, will also choose not to migrate. (b) An individual, who is indifferent between following his or her own signal and copying someone else's choice, will follow his or her own signal. (c) An individual, who is indifferent between following more than one of the previous migrants' decisions, will choose to randomize his or her decision with equal probabilities assigned to the different alternatives.

Consider three potential migrants. If neither of the first two individuals chose to emigrate, this means that neither received a signal. Individual 3 will copy them if and only if he does not receive a signal. Otherwise he will follow the signal he receives. If one of the first two individuals chose not to migrate and the other chose to migrate, individual 1 did not receive a signal and individual 2 did receive a signal. If individual 3 then receives a signal that indicates migration to the country to which the second individual has migrated, individual 3 will join the second migrant. Otherwise, if a signal different from that of individual 2 is received, individual 3 will follow his/her own signal. If individuals 1 and 2 have chosen to migrate to the same country, and individual 3 receives a signal to migrate to a different country, he will still migrate to the same country as individuals 1 and 2. In the following we will formalize this decision pattern.

Assume that individuals 1 and 2 emigrated to country j and individual 3 receives a signal to migrate to country k. Using the Bayesian rule, individual 3 can calculate the probability that the true signal is j out of m possible countries:[3]

$$\Pr(j \mid j, j, k) = \frac{p^3 q^2 (1-q) 1/m + p^2 (1-p) q \ (1-q) 1/m}{\Pr(j, j, k)}. \qquad (6)$$

Similarly, individual 3 can calculate the probability that the true signal is k:

$$\Pr(k|\,j,\,j,k)=\frac{p^3q(1-q)^2\,1/m+p^2(1-p)q(1-q)\;1/m}{\Pr(\,j,\,j,k)}\quad. \tag{7}$$

For $q > 0.5$,[4]

$$\Pr(\,j|\,j,\,j,k) > \Pr(k|\,j,\,j,k) \tag{8}$$

Hence, individual 3 will migrate to country *j* even though he received a signal to emigrate to country k. This is the basis of herd behavior.

Individuals will migrate following the herd (flow) while disregarding their own private information.[5,6]

2.3. Herd and Network effects

Herd and network effects may work together. Consider the case when one individual has chosen to migrate to a country. A second individual receives a positive signal indicating emigration to a different country. If the latter chooses to follow the first migrant, then she knows that all successors will follow for informational and payoff reasons (herd behavior and positive externalities). If she chooses the other country, there is a positive probability that she will end up alone. So, while she may think that the basic payoff or utility from moving to the alternative country is as good as for the first country, the awareness of the positive network payoff will induce her to choose the same location as the first emigrant. Herd behavior is therefore more pronounced than when externalities are absent, and with a high probability the first emigrant will be followed by everyone.

In the presence of beneficial externalities, the utility from migrating to a country depends on the stock of immigrants who have previously immigrated and how many people will migrate in the future. Hence, even if the wage in a country is relatively low, positive externalities may make that country an attractive location. Suppose, for example, that *n* people have migrated to country *j* and one individual to country *k*. In that

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[3] By definition, the probability *q* is normalized in regard to the two different locations.

[4] In the case of comparing two possibilities *q > 0.5* otherwise it will be always better to chose randomly then to use the information.

[5] For the general case see Epstein (2002).

[6] It may be the case that there is more than one herd going to alternative locations.

case a potential migrant might still choose to go to country *j*, even if the wages in *j* are lower than in country *k*.

With herd behavior, the probability that a signal received by an individual is true is a function of both the number of previous migrants that have migrated to the same country and the stock of immigrants who have chosen other locations. Suppose an individual has received a signal indicating that country *j* is best, and has to choose between country *j* and country *k*. The benefits from network externalities influences the probability that a signal is true via the relative number of migrants who previously immigrated to other countries. If there are positive network externalities, herd effects are more pronounced. If disadvantageous or negative externalities are present,[7] incentives arise to move to new locations, in the course of which individuals tend to reveal private information -- as they will only migrate to another location if warranted by private information. Informational herd effects are therefore less pronounced in the case of negative externalities.

On the other hand, due to herd behavior a migrant may move to a country where the marginal positive effect of the externalities is smaller than the marginal negative effect of the wage. In other words, a migrant might choose a specific location even if the stock of immigrants who have already migrated to this host country exceeds N_1 in Figure 3. A migrant, who is living in this host country, will now send negative signals to potential migrants in his home country. The local population in the home country, who receive these negative signals, however, observe that a lot of individuals have already migrated to this host country and may even receive other general information (such as news paper articles, television shows, etc.) that this place is the right place to migrate.

An individual who has to make a decision will weigh the information he receives: the stock of previous individuals who have migrated to that country (and to other countries), the general information he received, his observation on the flow of migrants and the negative information he received from the migrants who have already migrated to

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7 Gang, Rivera-Batiz and Yun (2002) provide a statistical analysis of the determinants of attitudes towards foreigners displayed by European sampled in the Eurobarometer surveys in 1988 and 1997. In general they show that those who compete against migrants in the labor market have more negative attitudes toward foreigners and, as the concentration of immigrants in the local population increases, the likelihood of negative attitude increases (a negative network externality effect). See also Bauer, Lofstrom and Zimmermann (2000).

that country. The individual knows that there is a positive probability that the information he received from the migrants in the host country is true for *them* as they do not want other migrants to join them (as this will decrease their utility when the stock migrants in the host country increases to N_2 in Figure 3). However, it may be optimal for the migrant to join them even if there are negative signals. Epstein (2002) shows that under such conditions, in order for the individual to follow the flow (herd), the proportion of negative signals relative to the stock of migrants must fall. In our case, if N_2 in Figure 3 is sufficiently high, migrants will continue to choose that host country. Thus the probability that a migrant will immigrate to that country will be Pr_1 and not Pr_2 (in Figure 3). Pr_2 is the probably of migrating to that country if the migrant considered only network externality and not the flow of immigrants migrating to that country.

Let us try to explain how we can distinguish between the stock-network and flow-herd effects. Assume we have two potential receiving countries, country A and B (see Table 1). Table 1, Example 1, shows a situation in which there is the same stock of migrants living in both countries. The herd (which is included in the stock), however, differs between the two countries. 100 individuals migrated to country A in the last year, while country B received 300 individuals. In terms of network-externalities the level of externalities in both countries are identical (both have a stock of 1,000 individuals) while the flows to both countries differ. If the migrant decides to go to country B it is clear that the decision is independent of the network-externality effect, since it is identical in both countries. In Example 2, the flow of migrants is identical for both countries while the stock differs. In this situation we would be able to identify network externalities. Both examples together show us how we can distinguish between herd effects and network externalities: Holding constant the stock of migrants enables us to identify the herd-flow effect, while holding fixed the flow of migrants helps us identify the stock-network effect.

3. THE GEOGRAPHIC DISTRIBUTION OF MEXICAN MIGRANTS IN THE US

We explore the herd and network effects of migration using individual level data on Mexican-U.S. migration collected by the Mexican Migration Project, a collaborative research project based at the University of Pennsylvania and the University of Guadalajara.[8] An ethno-survey approach, combining techniques of ethnographic fieldwork and representative survey sampling, is used for data collection. Interviews are generally conducted in December-January when sojourner U.S. migrants often return to Mexico. These are supplemented with surveys of out-migrants located in the United States. Massey and Zeteno (1999) show that the Mexican Migration Project data are a good source of reasonably representative retrospective data on documented and undocumented migration to the United States.

The data comprise more than 7,000 households in 52 communities. The communities are located in the states of Colima, Guanajuato, Guerrero, Jalisco, Michoacán, Nayarit, San Luis Potosí, and Zacatecas and have been selected based on their diversity in size, ethnic composition and economic development, not because they were known to contain U.S. migrants. Each year since 1987, two to five communities in these states are surveyed. Each community is surveyed only once. In general, 200 households in each community are selected through random sampling. If the community is small, fewer households are chosen. The data includes information on the socioeconomic characteristics of the household head, such as age, education and marital status, their migration histories including information on year of migration, costs of border crossing, documentation and location in the United States.

The key variables in our analysis are measures of migration networks (stock) and herds (flows). To calculate these variables we make use of an event-history file provided by the Mexican Migration Project. This event-history file contains detailed labor and family histories of each household head, for each year from the birth of the household head until the year of the survey.[9]

Using the migration duration information from this file, we calculated for each year *t* the cumulative migration experience (in months) of each migrant *i* from the

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[8] See Massey et. al. (1987), Massey, Goldring and Durand (1994), and Massey and Zenteno (1999) for descriptions of the data set. We use the MMP52 version of the data. The data is made available to users at www.pop.upenn.edu/mexmig/.

[9] See Donato, Durand and Massey (1992) for a description of the event-history file.

Mexican community m in each U.S. county j $(j=1,\ldots,J)$.[10] The cumulative migration experience of community m in U.S. county j, EXP_{mjt}, is

$$EXP_{mjT} = \sum_{t=0}^{T}\sum_{i=1}^{N} M_{mjit} \quad , \tag{9}$$

where M_{mjit} is a dummy variable that takes the value 1 if an individual i in the Mexican community m migrates to the U.S. county j at time t.

Our primary measure of network effects, NET_{mjt} or *Village Migration Experience*, is defined as the migration experience of a Mexican community in a particular U.S. location relative to the total U.S. migration experience of that Mexican community, in percent. The measure captures the concentration of a Mexican village's migration experience in a U.S. location at the time a person makes his migration decision. It is calculated as

$$\textit{Village Migration Experience} = NET_{mjt} = \frac{EXP_{mjt}}{\sum_{j=1}^{J} EXP_{mjt}} \cdot 100\,. \tag{10}$$

In addition to the migration experience of a particular Mexican village, we use the *Mexican share of the total population* in a certain U.S. location (see the Appendix for a description of the calculation of this variable). This second network variable disregards village network externalities, capturing the concentration of Mexican ethnic goods in a location relative to other locations. Adding this second network variable helps to distinguish a generalized network effect from the village-specific links.

Herd effects are proxied by the *flow* of migrants during the year before an individual migrates. This flow of migrants is calculated as the percentage difference in the stock of migrants in two consecutive years. An increasing flow to one location may increase the number of migrants that wish to go to that particular location. However, we are interested in the flow to a certain destination relative to other locations, since, according to our theory, herd behavior suggests that migrants should follow only the

10 We do not discount months over time, or for those who have returned to their village in Mexico. Although their knowledge of current labor market conditions may deteriorate, they provide key links and support for the network.

largest flow. Thus, we do not present the flows as absolute numbers but in relative terms. This enables us to see the increase/decrease in flow relative to other locations. We capture herd effects by looking at the change in *Village Migration Experience*, H_{mjt}, in the year before an individual migrates,

$$Herd = H_{mjt} = NET_{mjt} - NET_{mj(t-1)}\,. \tag{11}$$

This enables us to see how the relative flow of migrants between *t-1* and *t* affects the probability of migrating to a particular location at time *t*.

In order to control for other factors that may affect the utility levels associated with a U.S. location, we include several variables capturing the economic and social characteristics of a location in the multivariate analysis.[11] A detailed description of these variables is given in Appendix A. To control for job opportunities and the general level of economic activity, we include total population in a U.S. area. We also include the unemployment rate in a U.S. area in order to take account of both job opportunities and potential wages. The literature often assumes that the probability of choosing a particular location decreases with the unemployment rate in this location (see the discussion in Jaeger (2000)).

Migration costs have a direct effect on the location choice. Most Mexican migrants have a very low income in their home country and the cost of migrating may be an important issue in determining the specific location to migrate. In order to control for these costs we include road mileage from the migrant's origin village in Mexico to the alternative U.S. locations.[12]

The independent variables just discussed are U.S. location specific, as dictated by the conditional logit formulation we discuss in the next section. In addition we utilize several individual specific variables and examine how these individual dimensions

11 Ideally, we would like to include wages. What we would need is average wages by U.S. locations, comparable to our data set locations, for every year in our data set. This is a rather impossible task. Hence, we employ other variables (total population, unemployment rate) as proxies for wage possibilities.

12 In addition to road mileage, we also examined hours by car and the actual migration costs expressed by the migrant himself. All three cost variable yielded the same results in our estimations.

interact with our network and herd effect variables. In particular, we look at the interaction of the location specific variables with skill level, legal status and whether it is someone's first trip to the U.S. or their last trip (as recorded in the data). Migrants with six or less years of schooling are assumed to be unskilled, those with more than six years are considered to be skilled. Migrants report themselves whether they migrated legally (documented) or illegally (undocumented). We expect the migrant's use of networks or inclination to follow the herd will vary depending on these factors. In particular, we expect network and herd effects to vary between the first time an individual migrates to the U.S. and consecutive moves.

Table 2 presents a description of the data we use in our analysis. For the first migration, we have information on 1739 individuals from 47 Mexican villages who migrated to 43 different locations in the US. The U.S. locations vary in geographic unit, some are cities, some are parts of a county, and some are counties (See Appendices B and C for a list of the locations). We assume that each person has the possibility of going to each of these 43 locations, but does not consider other locations. This generates 74,777 observations – each person may or may not go to each of the 43 locations. For the last migration, we have 1561 individuals from 47 Mexican villages going to 46 U.S. locations, resulting in 71,806 observations. Unskilled migrants dominate, comprising 67% of first time migrants and 74% of last time migrants. On the other hand, 88% of first time migrants are undocumented, while only 46% of repeat migrants are undocumented. It appears that Mexicans obtain U.S. residence permits over time.

Table 2 further indicates that Mexicans make up about 5.5% of the population of the U.S. locations in our sample. The highest concentration could be observed in Laredo, Texas, where 24.2% of the residents are of Mexican origin (Appendix B). Laredo has the highest unemployment rate in our sample (over 16%), a very small local population and is very close to Mexico. Even though the city is small and has a high unemployment rate many appear to migrate there, as migration costs are relatively low. Our *Village Migration Experience* variable averages 1.9%. It reaches a maximum of 29.2% in Los Angeles, followed by Chicago with 9.2% (Appendix B). The herd effect appears to be about twice as large for first time migrants than for repeat migrants. Each of our locations has, on average, an unemployment rate of 7.1%, a population of 1.35 million, and is approximately 1460 miles away from the sending village in Mexico.

Figures 4 and 5 describe some typical patterns of our two network variables. In Figure 4 we plot the Herfindahl index of the concentration of the U.S. migration experience of nine typical Mexican villages for the time period covered in our sample. The index is given by

$$HERF_{mt} = \sum_{j} \left(\frac{NET_{mjt}}{100} \right)^{2} \tag{12}$$

with $0 \leq HERF_{mt} \leq 1$. Higher values of $HERF_{mt}$ indicate a higher concentration of the migration experience of a Mexican village. The villages differ in their overall concentration of their migration experience. Compared to the other villages depicted in Figure 4, the concentration is relatively low in the community 36 and 38 in the Mexican State S.L.P., community 46 in the state Zacatecas, and community 33 in the state Colima.[13] In most of the nine villages the concentration of the migration experience is increasing over time and flattens out at the end of the sample, indicating some kind of quadratic pattern, even though most of the villages do not reach a turning point. Only in community 36 we observe a pattern, where the concentration of the migration experience is increasing at the very beginning of the sample period, reaches a maximum and then decreases again. In contrast to all other communities we observe an U-shaped pattern in community 52 in the Mexican state Oaxaca. Note that we find such a pattern only in two communities.

Figure 5 shows the development of our second network variable, the share of the Mexican population, in six U.S. locations for the period covered in our sample. Los Angeles County is the location with the highest average value of the other network variable, the migration experience of a particular Mexican village. Imperial Valley, Chicago, Houston, and Miami are chosen for their geographical dispersion and generic interest. In all these five U.S. locations the share of the Mexican population is increasing. The sixth U.S. location is Laredo in Texas, which has the highest average share of

Mexican population in our sample. In Laredo, the share of the Mexican population shows an U-shaped pattern over time; it is decreasing until 1982 and then increasing again.

4. MULTIVARIATE ANALYSIS

4.1. Econometric Approach

In the econometric analysis we estimate a conditional logit model (McFadden, 1973, 1974).[14] Each Mexican migrant *i* faces a choice among *J* alternative U.S. communities. Assume that the utility of choosing location j is given by

$$U_{ij} = X_j \beta + \varepsilon_{ij}, \tag{13}$$

where X_j is a vector of the characteristics of the U.S. community *j,* including herd and network effects, and ε_{ij} is an error term that is assumed to be independent and identically distributed with a Weibull distribution. Individual *i* is assumed to maximize his utility. The probability that an individual *i* chooses community *j* is given by

$$\Pr(U_{ij} > U_{ik}) \quad \text{for all} \quad k \neq j. \tag{14}$$

Let Y_i be a random variable that takes the values 0 and 1 indicating the location choice made by the migrant. The probability that individual *i* chooses the U.S. community *j* can then be written as

$$\Pr(Y_i = j) = \frac{exp(X_j \beta)}{\sum_{j=1}^{J} exp(X_j \beta)}, \tag{15}$$

where X_j is a vector of characteristics of the U.S. communities in our sample and β is a parameter vector. Equation (15) can be estimated using maximum likelihood. Note that

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13 Unfortunately, the data set does not provide names for the different villages.

14 Bartel (1989) and Jaeger (2000) also use this model to study the location choice of migrants in the United States.

our sample is restricted to individuals who actually migrated at some point in time to the U.S. The analysis does not consider migration within Mexico.

As discussed in Section III, our estimations include two measures of the effect of the stock of migrants (network externalities), i.e., the Mexican share of the total population in U.S. location *j* and the migration experience of a Mexican village *m* in the U.S. location *j*, NET_{mjt}, a measure of the flow of migrants which capture herd effects, H_{mjt}, the total population and unemployment rate in U.S. location *j*, and the cost of migration measured as the road mileage distance between Mexican village *m* and U.S. location *j*. All variables, with the exception of the network variables, enter linearly. The theory we developed in Section II shows us that we should expect the network variables, *Village Migration Experience* and the *Mexican share of the population*, to have an inverse U shape relationship with the probability of migrating to a certain location. Hence, our specification of equation (15) includes both a linear and a squared term of the two network variables.

In our empirical analysis we consider different specifications of equation (15). As individuals may have migrated more than once to the U.S., we divide our analysis into two parts: first and last migration. In the former we consider only the location decision made by the Mexican migrants at his/her first time migrating to the U.S. while the latter considers only the location decisions made at his/her last time migrating to the U.S., conditional that he/she migrated to the U.S. at least once before. For both specifications we estimate an overall (constrained) equation and an unconstrained equation. In the latter all variables considered in the basic specification are fully interacted with four dummy variables, one for unskilled illegal migrants, one for unskilled legal migrants, one for skilled illegal migrants, and one for skilled illegal migrants.

4.2. Estimation Results

The second column of Tables 3 and 4 present the results for the constrained model and columns 3-6 the results for the unconstrained model for the first and last migration decision, respectively. Consider first the results for the constrained specification for the first migration decision. The Mexican share in the population of a U.S. location appears to have an inverted U-shaped effect on the probability of choosing a particular location.

Evaluated at the sample mean of a Mexican population share of 5.51%, the average marginal effect of an increase of the population share by one percent is 0.15.[15] Figure 6(a) shows the predicted effect of the share of Mexicans in the population of an average U.S. location on the probability of choosing that location.[16] The effect strongly follows an inverted U-shaped pattern, reaching a peak at a population share of about 10%.

Our second network variable, the migration experience of a Mexican village, also follows an inverted U-shaped pattern. The simulation in Figure 6(b) shows that this pattern is less pronounced than for the Mexican population share. Up to a share of the migration experience of a village in a particular U.S. location to the total migration experience of about 63% the effect of this variable on the probability to choose a U.S. location is positive. In our sample we observe only four U.S. locations where the value of NET_{mjt} exceeds 63%: Los Angeles County, Orange County and San Diego County in California as well as Chicago.[17] The coefficient on the variable capturing herd effects is significantly positive. The average marginal effect for this variable is calculated to be 0.0053, indicating that a 1% increase in the flow of migrants to a specific U.S. location in the last year increases the probability that a migrant chooses this location on average by 0.53%. The simulated effect of different values of H_{mjt} on the probability to choose a U.S. location is shown in Figure 6(c).

Similar to the constrained model, the Mexican share in the population of a U.S. location has an inverted U-shaped pattern on all four subgroups considered in the unconstrained model. It appears that the Mexican network in a U.S. location is more important for unskilled as compared to skilled workers. Whereas the probability of choosing a U.S. location peaks at a Mexican population share of about 10% for the latter,

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15 The marginal effects of a change in the characteristics X_j of a U.S. location j on the probability that a Mexican migrant will choose location j are given by the derivative of equation (15) with respect to the characteristics X_j. Note that these marginal effects will vary with the characteristics of a U.S. location j. Therefore, we follow the approach chosen by Jaeger (2000) and calculate average effects of a change in the characteristics X on $Pr(Y_i = j)$, i.e. $\partial Pr(Y_i = j)/\partial X_j = [(1/J)(1-(1/J))]\hat{\beta}$, where J=43 for the first migration decision and J=47 for the last migration decision. Hence, to obtain average marginal effects, the coefficients reported in Table 3 have to be multiplied by 0.0227 and those in Table 4 by 0.0208.

16 In particular, we calculated $Pr(Y_i = 1) = \dfrac{exp(\beta' X_j)}{1 + exp(\beta' X_J)}$ using sample means for X_j for all variables except the variable of interest and assuming that the location specific fixed effects are zero.

it reaches a maximum for skilled workers already at a population share of 8%. Comparing legal and illegal migrants, however, no clear pattern emerges. As in the constrained model, the estimated inverted U-shaped pattern for the village experience variable is much flatter than the respective pattern for the Mexican population share. However, in contrast to the Mexican population share, important differences between legal and illegal migrants appear. For illegal migrants, the effect of village migration increases the average probability of choosing a U.S. location up to a share of 61% for unskilled, and 71% for skilled. For legal migrants this variable reaches its maximum effect at a share of 48% for unskilled and a share of 53% for skilled migrants. Herd effects have a significant effect on all sub-groups considered. It further appears that there are no significant differences of the estimated herd effect between the different groups. Finally, our results suggest that the illegal migrants response is more sensitive to changes in the migration flow prior to their migration decision than are legal migrants. However, as already noted above, these differences are not statistically significant. Overall, these results indicate that legal and skilled migrants are less dependent on network externalities when deciding on the location. The results further suggest that village-specific links, captured by the migration experience of a village, are on average relatively more important for the location choice of a migrant than ethnic goods, captured by the Mexican population share.

The estimation results for the last migration decision are reported in Table 4. The simulated effect of the network and herd variables for the average U.S. location on the probability to choose that location are shown in Figure 7 for the constrained model. Similar to the first migration decision, both network variables appear to have an inverted U-shaped pattern on the probability of choosing a U.S. location and the pattern of the effect is much flatter for the village migration experience as compared to the share of the Mexican population in a U.S. location. Comparing the different groups differentiated in the unconstrained model does not give a significantly different picture than the one obtained in Table 3. Comparing the first and last migration decision, however, it appears that both network and herd effects are slightly more important for the last migration decision. Comparing the simulated patterns in Figure 7 to those in Figure 6, the peaks are at a higher probability level and a higher share for the two network variables in the

[17] This only happened in certain years and does not show up in the Appendix tables.

former. The effect of the herd variable on the probability of choosing a U.S. location is steeper for the last as compared to the first migration decision.

Let us finally consider the results on the characteristics of the U.S. location. In the constrained model, the unemployment rate in a U.S. location has a negative effect on the probability of choosing this location. However, only for the migrants first trip is this effect statistically significant. In the unconstrained model, the effect of the unemployment rate on the location decision of a migrant is unclear for his/her first trip. According to the results reported in Table 3, the unemployment rate has a significant negative impact on the location decision of skilled illegal migrants and an unexpected significant positive impact on unskilled legal migrants. For the last trip of a migrant, the unemployment rate in the U.S. location *j* affects only the location choices of skilled migrants on a statistically significant level; an increase in the unemployment rate in a U.S. location decreases the probability that a skilled Mexican migrates there by 0.4 percent for illegal migrants and by 0.2 percent for legal migrants.

The probability that migrants choose a particular U.S. location increases with the total population in that location for the first trip. For the last trip the total population has a positive effect on the location choice of unskilled illegal and skilled migrants, and a negative effect on unskilled legal migrants. This result reflects that migrants prefer to move to regions with a relatively large labor market, which increases the probability to find a job and to receive relatively higher wages. The distance between the home community and the U.S. location has a negative impact on illegal migrants and a positive impact on documented migrants on their first trip; the estimated coefficients are, however, not statistically significant at the 5%-level. For the last migration decision the distance to the U.S. location shows an unexpected pattern. For the constrained model as well as for unskilled workers in the unconstrained model the coefficient of the distance variable is significantly positive indicating that a higher distance increases the probability of choosing a U.S. location. It might be that this variable captures some other effects of characteristics of the U.S. locations we could not control for in our specification.

Our empirical results show that, as presented in the theoretical part of the paper, both network-externalities and herds have significant effects on the migrant's decision on where to migrate. We should and cannot neglect both effects when making our analysis of the choice of a location to choice. These results confirm and extend other results on the importance of networks in location choice (for example, Jaeger (2000), and Winters, de Janvry and Sadoulet (2001)). Moreover, the village network externality effect has an inverse U shape and not only a positive linear effect as many times presented in the analyses in the literature.

5. CONCLUSION

Immigrant clustering is an important phenomenon to study for a number of reasons. The process by which immigrants make their decisions of where to locate is one that is not clearly understood, though there is much research on the subject. The standard economic theory is the network story that argues that there are significant externalities, or "ethnic capital", of which immigrants wish to take advantage. They move to where members of their community had previously gone, planning to avail themselves of these externalities. The herd effects story argues something quite different, and minimizes the importance of externalities in the migration process. Herd behavior offers an information perspective on why emigrants from the same location make the same foreign relocation decision. To the extent we are able to distinguish between herd and network phenomena, we have important insights into understanding migrants' location choices. This can then influence policies of receiving countries, and well as host countries.

In our theoretical model we present a framework encompassing both network and herd effects. Herd behavior is conceptually different and distinguishable from migration that is motivated by network externalities. Network and herd effects reflect different types of information. Migrants might be motivated to choose a location in order to benefit from the network externalities it has to offer. However, as a result of herd behavior, the migrant may choose a location on the supposition that recent previous migrants had information that he does not have. Migrants may choose to follow the flow, which is to migrate to the location recent migrants have been observed to choose. There is also no reason why herd effects and network externalities should not be simultaneously present to influence emigration location decisions. Herds may be an explanation for the creation of the mass of immigrants that is sufficient to attract others to join and enjoy the positive externalities of the network. Informational cascades also help us understand why we observe immigrants deciding to migrate to destinations where the negative externalities are stronger than the positive externalities of the network. The reason for this phenomenon is that individuals are uncertain regarding the effect of the network externalities and decide to follow the flow of migrants rather than the stock of immigrants. Finally, herd behavior enables us to understand how an individual makes a decision when there is more than one country that provides the immigrant with the same level of network externalities. Immigrants will decide to follow the flow (herd behavior) of immigrants.

We use data from the Mexican Migration Project to investigate the location decision of Mexican migrants in the U.S. We distinguish between two types of network effects, capturing general ethnic goods available in a U.S. location on the one hand, and origin village connections and the history of the migration experience of a village in different U.S. locations on the other hand. Using these two variables helps us to distinguish a generalized network effect from village-specific links. Herd effects are measured using the flow of migrants to a particular U.S. location during the year prior to the migration decision of an individual.

We show that both network externalities and herds have a significant effect on the migrant's location decision. Moreover, the significance and size of the effects vary according to the legal status of the migrant and whether the migrant is a "new" or a "repeat" migrant. The estimated network effects show an inverse U-shape pattern, not a linear positive effect as often presented in the literature. The results indicate that village-specific links are relatively more important for the location decision of a migrant than the availability of ethnic goods. Furthermore, legal and skilled migrants appear to be less dependent on network externalities than illegal and unskilled migrants. Herd effects have significant positive effects on the location decision of a migrant. Our empirical estimations indicate, however, that there are no significant differences of these herd effects between different types of migrants.

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Table 1:
Examples of Stocks vs. Flows in Migration

	Example 1		Example 2	
	A	B	A	B
Network (stock)	1000	1000	500	700
Herd (flow)	100	300	100	100

Table 2:
Descriptive Statistics, Means of U.S. Recipient Locations

		First Migration	Last Migration
Unemployment Rate (in %)		7.103	7.310
		(3.309)	(3.413)
Total Population (in 100,000)		13.351	14.066
		(18.867)	(19.216)
Miles		1459.956	1431.984
		(527.774)	(510.941)
Mexican Share of Population (in %)		5.511	5.568
		(6.476)	(6.163)
Village Migration Experience (in %)		1.986	1.870
		(7.622)	(7.563)
Herd (in %)		0.878	0.442
		(46.054)	(26.340)
Unskilled Legal	(Observations)	3784	22908
	(Individuals)	88	498
Unskilled Illegal	(Observations)	46268	30360
	(Individuals)	1076	660
Skilled Legal	(Observations)	5289	11040
	(Individuals)	123	240
Skilled Illegal	(Observations)	19436	7498
	(Individuals)	452	163
Total	(Observations)	74777	71806
	(Individuals)	1739	1561
Number of Mexican Villages		47	47
Number of U.S. locations		43	46

Note: Standard deviations in parentheses.

Table 3:
Conditional Logit Analysis of Mexican Migrants' Location Choices:
First Migration

	Constrained	**Unconstrained**			
		Unskilled		**Skilled**	
Variables		**Illegal**	**Legal**	**Illegal**	**Legal**
Mexican Share of Population (in %)	0.154**	0.126**	0.210**	0.280**	0.262**
	(0.019)	(0.022)	(0.083)	(0.057)	(0.099)
Mexican Share of Population (in %)^2	-0.008**	-0.006**	-0.010**	-0.017**	-0.017**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.006)
Village Migration Experience (in %)	0.110**	0.113**	0.122**	0.100**	0.137**
	(0.005)	(0.006)	(0.025)	(0.009)	(0.019)
Village Migration Experience (in %)^2*10^{-2}	-0.087**	-0.092**	-0.126**	-0.070**	-0.130**
	(0.006)	(0.008)	(0.038)	(0.011)	(0.027)
Herd	0.233**	0.228**	0.155**	0.295*	0.213*
	(0.025)	(0.030)	(0.089)	(0.056)	(0.117)
Unemployment Rate (in %)	-0.033*	-0.001	0.087**	-0.177**	0.053
	(0.014)	(0.017)	(0.065)	(0.034)	(0.057)
Total Population (in 100,000)	0.012**	0.009**	0.021**	0.018**	0.015**
	(0.001)	(0.002)	(0.005)	(0.003)	(0.005)
Miles (in 1,000)	-0.039	-0.026	0.256	-0.296*	0.148
	(0.077)	(0.096)	(0.370)	(0.164)	(0.313)
Log-likelihood	-4025.0	-3979.5			
Pseudo-R^2	0.385	0.392			

Note: Observations: 74,777. Standard errors in parentheses. * : Statistically significant at least at 10% level. ** : Statistically significant at least at the 5% level.

Table 4:
Conditional Logit Analysis of Mexican Migrants' Location Choices: Last Migration

	Constrained	Unconstrained			
		Unskilled		Skilled	
Variables		Illegal	Legal	Illegal	Legal
Mexican Share of Population (in %)	0.191**	0.120**	0.248**	0.322**	0.378**
	(0.021)	(0.029)	(0.044)	(0.098)	(0.079)
Mexican Share of Population (in %)^2	-0.008**	-0.005**	-0.011**	-0.019**	-0.020**
	(0.001)	(0.001)	(0.002)	(0.006)	(0.005)
Village Migration Experience (in %)	0.150**	0.129**	0.209**	0.095**	0.134**
	(0.006)	(0.009)	(0.010)	(0.015)	(0.014)
Village Migration Experience (in %)^2*10^{-2}	-0.135**	-0.110**	-0.214**	-0.068**	-0.118**
	(0.008)	(0.011)	(0.015)	(0.020)	(0.019)
Herd	0.380**	0.357**	0.395**	0.451**	0.438**
	(0.046)	(0.063)	(0.091)	(0.140)	(0.146)
Unemployment Rate (in %)	-0.024	-0.002	0.005	-0.188**	-0.074*
	(0.015)	(0.020)	(0.026)	(0.063)	(0.045)
Total Population (in 100,000)	-0.0001	0.004*	-0.011**	0.023**	0.009**
	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)
Miles (in 1,000)	0.329**	0.220*	0.483**	-0.243	0.386
	(0.088)	(0.125)	(0.174)	(0.280)	(0.242)
Log-likelihood	-3450.0	-3375.8			
Pseudo-R^2	0.423	0.435			

Note: Observations: 71,806. Standard errors in parentheses. * : Statistically significant at least at 10% level. ** : Statistically significant at least at the 5% level.

Appendix A: Data description

Total Population:
Data for selected years between 1970 and 1995 were obtained from periodic Census publications, such as the CPS and County and City Yearbook. Data were obtained for the following years: 1970, 1974, 1976, 1977, 1980, 1984, 1986, 1987, 1990, and 1991. The population for the intercensual years was estimated by assuming an exponential growth function. To estimate the population between 1992-1995, the constant growth rate that prevailed between 1980 and 1991 was applied. Source: *Mexican Migration Project 52*.

Mexican Share of Population:
This variable has been obtained from the U.S. Census Bureau for the censual years 1970, 1980 and 1990. A second-degree polynomial equation was estimated to these three data points to estimate the size of the Mexican foreign-population in each area during the inter-censual years. To estimate the Mexican foreign-born population in the years 1991-1995, it has been assumed that the annual growth rate during this period is the same as the annualized constant growth rate in each area between 1980 and 1990. The size of the Mexican foreign-born population is divided by the *Total Population* in a U.S. location. Source: We are very grateful to Julie A. Phillips for making this variable available to us.

Unemployment Rate:
The most recent information on the number unemployed and the size of the civilian labor force at the county level was obtained for the years 1974 and 1976-1996 from the Bureau of Labor Statistics, Local Area Unemployment Statistics Division. For the early 1970s, no information by county is available although information on unemployment for the censual years 1960 and 1970 is available. For the years 1971-1973, the assumption was made that unemployment rates in a county follow the same trends as that of the state. An estimate of the unemployment rate for 1975 was obtained by averaging the unemployment rates for 1974 and 1976. Source: *Mexican Migration Project 52.*

Migration Costs:
We collected data on three measures of migration costs. For *Miles* and *Hours* we entered in the main town in the Mexican state in which the origin village is located and the main town in the U.S. location into *Mapquest* (www.mapquest.com) and into *Mapblast* (www.mapblast.com). For *Actual Costs* the data come from the *Mexican Migration Project 52*. Since the actual cost data was very sketchy, we decided not to use it. Trials with the *Hours* and the *Actual Costs* data yielded similar results to those when we used *Miles*.

Village Migration Experience and Herd:
These variables were calculated as indicated in the text from the event history file. *Source: Mexican Migration Project 52.*

Skilled vs. Unskilled, Legal vs. Illegal:

All migrants with less than 7 years of schooling are considered to be unskilled, those with more than 6 years of schooling are considered to be skilled. Undocumented migrants are labeled illegal, documented migrants *legal*. Source*: Mexican Migration Project 52*.

Appendix B: Descriptive Statistics by U.S. Receiving County: First Migration

	Unemployment Rate	Total Population (in 100.000)	Miles	Mexican Share of Population (in %)	Village Migration Experience (in %)
Imperial Valley, CA	9.767	8.407	1828.160	8.137	1.703
	(2.491)	(2.603)	(160.834)	(1.533)	(5.863)
Lower San Joaquin, CA	9.573	4.278	1828.160	6.201	0.532
	(2.267)	(0.812)	(160.834)	(1.059)	(1.421)
Middle San Joaquin, CA	10.217	5.328	1828.160	7.957	2.496
	(2.192)	(0.857)	(160.834)	(1.773)	(3.548)
Upper San Joaquin, CA	11.752	7.940	1828.160	5.687	3.731
	(2.183)	(1.558)	(160.834)	(1.148)	(8.151)
Salinas-Monterey-Santa Cruz, CA	7.538	10.260	1996.099	7.474	2.934
	(2.031)	(1.676)	(160.467)	(0.513)	(4.492)
Sacramento Valley, CA	7.632	16.661	1996.099	3.134	2.377
	(2.162)	(3.029)	(160.467)	(0.534)	(3.661)
Ventura-Oxnard-Simi, CA	7.213	5.356	1608.970	7.465	1.875
	(1.314)	(0.957)	(160.619)	(0.858)	(3.747)
Santa Barbara, CA	6.056	3.121	1608.970	5.937	1.320
	(0.944)	(0.352)	(160.619)	(2.144)	(2.899)
Napa-Sonoma, CA	6.392	4.005	1996.099	2.256	0.893
	(1.899)	(0.676)	(160.467)	(1.050)	(2.686)
Los Angeles County, CA	6.866	77.237	1608.970	10.041	29.241
	(1.283)	(7.279)	(160.619)	(2.079)	(24.917)
Orange County, CA	4.856	19.621	1608.970	5.638	4.932
	(1.127)	(2.995)	(160.619)	(2.391)	(9.727)
San Francisco Urban Area, CA	5.586	33.490	1996.099	2.099	1.206
	(1.710)	(2.163)	(160.467)	(0.465)	(3.185)
San Jose Urban Area, CA	5.646	13.021	1996.099	3.713	2.595
	(0.966)	(1.345)	(160.467)	(0.921)	(6.343)
Riverside-San Bernardino, CA	7.241	17.184	1608.970	4.952	0.856
	(2.315)	(5.212)	(160.619)	(1.701)	(1.689)
San Diego County, CA	6.533	19.309	1608.970	5.490	5.184
	(1.488)	(3.758)	(160.619)	(1.374)	(12.782)
Rio Vista, CA	7.515	2.478	1996.099	1.737	0.067
	(1.397)	(0.594)	(160.467)	(0.245)	(0.314)
Abilene, TX	4.694	1.125	940.678	1.351	0.181
	(1.995)	(0.089)	(149.496)	(0.458)	(0.882)
Austin, TX	4.307	6.984	940.678	1.674	0.209
	(1.418)	(1.505)	(149.496)	(0.575)	(0.989)
Beaumont-Port Arthur, TX	8.069	3.671	940.678	0.561	0.091
	(3.559)	(0.136)	(149.496)	(0.102)	(0.581)
Brownsville, TX	11.093	2.125	621.961	21.255	1.313
	(2.788)	(0.440)	(134.766)	(5.922)	(2.760)
Bryan-College, TX	3.807	0.957	940.678	1.421	0.026
	(1.155)	(0.236)	(149.496)	(0.482)	(0.141)
Corpus Christi, TX	7.032	3.290	621.961	4.124	0.380
	(2.548)	(0.288)	(134.766)	(2.181)	(1.852)

Appendix B: continued

Dallas-Ft.Worth, TX	4.366	31.542	940.678	2.216	2.705
	(1.370)	(5.828)	(149.496)	(1.028)	(6.872)
El Paso, TX	9.263	4.906	1036.457	20.713	0.074
	(2.087)	(0.794)	(154.082)	(3.998)	(0.224)
Galveston, TX	6.904	1.997	940.678	1.835	0.128
	(3.031)	(0.165)	(149.496)	(0.668)	(1.079)
Houston, TX	5.317	30.412	940.678	3.791	3.782
	(2.430)	(5.510)	(149.496)	(0.969)	(8.975)
Laredo, TX	16.013	1.448	621.961	24.189	0.037
	(4.430)	(0.330)	(134.766)	(6.569)	(0.234)
McAllen, TX	14.252	2.946	621.961	22.815	1.030
	(4.765)	(0.743)	(134.766)	(6.316)	(2.370)
Odessa-Midland, TX	5.230	2.052	1036.457	3.399	0.125
	(2.748)	(0.340)	(154.082)	(0.319)	(0.669)
San Antonio, TX	5.668	11.520	940.678	6.203	1.369
	(1.621)	(1.486)	(149.496)	(2.580)	(3.491)
Victoria, TX	5.259	1.722	940.678	1.458	0.300
	(1.577)	(0.148)	(149.496)	(0.623)	(1.123)
Chicago, IL	6.398	73.705	2033.580	2.461	9.197
	(1.896)	(1.345)	(149.848)	(0.766)	(17.617)
Las Cruces, NM	7.715	1.029	1298.042	11.449	0.080
	(1.030)	(0.237)	(152.066)	(2.955)	(0.315)
Tucson, AZ	5.462	5.320	1238.160	4.378	0.153
	(1.437)	(1.003)	(160.834)	(1.437)	(0.816)
Phoenix, AZ	5.401	15.676	1238.160	2.592	0.762
	(1.368)	(3.832)	(160.834)	(0.836)	(2.612)
Denver-Boulder, CO	5.240	7.615	1605.164	1.328	0.240
	(1.468)	(2.462)	(144.481)	(0.438)	(0.616)
Reno, NV	5.629	1.923	1524.070	1.550	0.263
	(1.230)	(0.444)	(160.925)	(1.557)	(1.770)
Las Vegas, NV	6.909	5.533	1524.070	1.421	0.365
	(1.672)	(1.822)	(160.925)	(0.606)	(1.173)
Omaha, NE	4.398	1.766	1687.938	6.046	0.095
	(1.133)	(1.787)	(149.981)	(7.250)	(0.347)
New York City, NY	7.246	73.383	2596.999	0.205	0.375
	(2.371)	(2.263)	(129.604)	(0.188)	(1.413)
Washington D.C., WA	7.344	6.581	2386.269	0.085	0.059
	(1.922)	(0.489)	(132.258)	(0.033)	(0.296)
Miami, FL	6.954	16.210	1926.681	0.324	0.066
	(1.849)	(2.128)	(132.039)	(0.121)	(0.293)
Atlanta, GA	5.073	10.963	1749.061	0.208	0.042
	(1.586)	(0.681)	(132.803)	(0.282)	(0.315)
Total	7.103	13.351	1459.956	5.511	1.986
	(3.309)	(18.867)	(527.774)	(6.476)	(7.622)

Observations per U.S. county: 1739; Total observations: 74777.

Appendix C: Descriptive Statistics by U.S. Receiving County: Last Migration

	Unemployment Rate	Total Population (in 100.000)	Miles	Mexican Share of Population (in %)	Village Migration Experience (in %)
Imperial Valley, CA	10.019	10.887	1805.511	9.201	1.463
	(2.265)	(3.172)	(128.499)	(1.665)	(5.367)
Lower San Joaquin, CA	10.889	4.991	1805.511	7.142	0.625
	(2.350)	(0.870)	(128.499)	(1.391)	(1.179)
Middle San Joaquin, CA	11.381	6.092	1805.511	9.139	2.618
	(2.165)	(0.940)	(128.499)	(2.066)	(3.107)
Upper San Joaquin, CA	12.188	9.324	1805.511	6.776	4.410
	(2.032)	(1.689)	(128.499)	(1.479)	(10.385)
Salinas-Monterrey-Santa Cruz, CA	7.774	11.598	1973.522	7.932	2.798
	(1.684)	(1.591)	(128.294)	(0.689)	(4.014)
Sacramento Valley, CA	7.802	19.363	1973.522	3.429	2.095
	(1.773)	(3.299)	(128.294)	(0.575)	(2.715)
Ventura-Oxnard-Simi, CA	6.951	6.126	1586.325	8.177	2.670
	(1.375)	(0.914)	(128.400)	(1.111)	(5.449)
Santa Barbara, CA	5.831	3.436	1586.325	7.992	1.890
	(1.094)	(0.386)	(128.400)	(2.866)	(3.975)
Napa-Sonoma, CA	5.901	4.563	1973.522	3.264	1.463
	(1.557)	(0.668)	(128.294)	(1.340)	(4.713)
Los Angeles County, CA	6.949	83.756	1586.325	11.916	30.545
	(1.596)	(7.899)	(128.400)	(2.315)	(24.412)
Orange County, CA	4.602	22.118	1586.325	7.887	4.562
	(1.251)	(2.998)	(128.400)	(2.882)	(8.758)
San Francisco Urban Area, CA	5.233	35.446	1973.522	2.539	1.175
	(1.348)	(2.393)	(128.294)	(0.623)	(2.580)
San Jose Urban Area, CA	5.300	14.100	1973.522	4.421	2.213
	(1.077)	(1.289)	(128.294)	(1.173)	(6.033)
Riverside-San Bernardino, CA	7.476	22.107	1586.325	6.448	0.920
	(2.032)	(6.221)	(128.400)	(2.143)	(1.453)
San Diego County, CA	5.977	22.546	1586.325	6.794	5.801
	(1.454)	(3.890)	(128.400)	(1.690)	(15.218)
Rio Vista, CA	7.018	3.014	1973.522	1.930	0.087
	(1.393)	(0.657)	(128.294)	(0.299)	(0.328)
Abilene, TX	5.543	1.174	918.260	1.731	0.252
	(1.642)	(0.068)	(133.864)	(0.635)	(1.200)
Amarillo, TX	4.847	1.847	1157.821	1.616	0.107
	(1.194)	(0.146)	(134.139)	(0.886)	(0.521)
Austin, TX	4.752	8.237	918.260	2.098	0.177
	(1.248)	(1.510)	(133.864)	(0.721)	(1.066)
Beaumont-Port Arthur, TX	9.060	3.682	918.260	0.588	0.097
	(2.799)	(0.100)	(133.864)	(0.093)	(0.601)
Brownsville, TX	12.328	2.451	604.505	20.797	0.794
	(2.155)	(0.390)	(126.000)	(4.099)	(1.978)
Bryan-College, TX	4.071	1.121	918.260	1.817	0.020
	(1.094)	(0.201)	(133.864)	(0.650)	(0.082)
Corpus Christi, TX	8.169	3.465	604.505	3.613	0.223
	(2.152)	(0.229)	(126.000)	(1.414)	(1.188)

Appendix C: continued

Dallas-Ft.Worth, TX	5.114	36.443	918.260	3.214	3.142
	(1.164)	(5.902)	(133.864)	(1.324)	(8.955)
El Paso, TX	10.156	5.551	1012.657	20.871	0.059
	(1.460)	(0.772)	(133.075)	(2.936)	(0.153)
Galveston, TX	7.803	2.117	918.260	1.705	0.160
	(2.234)	(0.150)	(133.864)	(0.430)	(1.345)
Houston, TX	6.120	34.397	918.260	4.741	3.309
	(1.939)	(4.840)	(133.864)	(1.258)	(8.157)
Laredo, TX	16.912	1.721	604.505	24.742	0.024
	(3.217)	(0.331)	(126.000)	(4.995)	(0.138)
McAllen, TX	17.086	3.533	604.505	22.232	0.579
	(3.884)	(0.701)	(126.000)	(4.306)	(1.445)
Odessa-Midland, TX	6.289	2.229	1012.657	3.531	0.048
	(2.363)	(0.259)	(133.075)	(0.360)	(0.332)
San Angelo, TX	5.015	1.395	1012.657	4.359	0.111
	(1.137)	(0.105)	(133.075)	(0.760)	(0.472)
San Antonio, TX	6.147	12.716	918.260	5.716	0.815
	(1.364)	(1.427)	(133.864)	(1.677)	(2.190)
Victoria, TX	5.897	1.831	918.260	2.055	0.252
	(1.338)	(0.131)	(133.864)	(0.875)	(1.174)
Chicago, IL	6.521	74.754	2011.131	3.163	8.350
	(1.456)	(1.295)	(134.142)	(0.873)	(16.917)
Tucson, AZ	5.030	6.102	1215.511	4.733	0.111
	(1.246)	(0.934)	(128.499)	(1.250)	(0.551)
Phoenix, AZ	5.084	18.915	1215.511	3.198	0.402
	(1.110)	(3.869)	(128.499)	(1.038)	(1.352)
Denver-Boulder, CO	5.456	8.437	1583.517	1.680	0.211
	(1.098)	(3.109)	(127.860)	(0.695)	(0.422)
Pueblo, CO	8.673	1.244	1583.517	0.857	0.158
	(2.370)	(0.017)	(127.860)	(0.410)	(1.058)
Reno, NV	5.403	2.289	1501.444	3.058	0.368
	(1.006)	(0.438)	(128.591)	(2.160)	(2.306)
Las Vegas, NV	6.426	7.201	1501.444	1.976	0.251
	(1.501)	(2.100)	(128.591)	(0.718)	(0.934)
St. Louis, MO	5.614	14.196	1549.915	0.069	0.063
	(1.324)	(0.434)	(134.021)	(0.017)	(0.210)
Omaha, NE	3.992	1.551	1665.505	5.543	0.157
	(1.168)	(1.679)	(134.353)	(6.134)	(0.460)
New York City, NY	7.469	73.164	2578.455	0.390	0.265
	(2.047)	(1.464)	(120.590)	(0.266)	(1.148)
Washington D.C., WA	7.281	6.264	2367.655	0.114	0.053
	(1.733)	(0.393)	(123.929)	(0.034)	(0.256)
Miami, FL	7.307	17.999	1908.071	0.436	0.056
	(1.630)	(2.156)	(123.611)	(0.142)	(0.194)
Atlanta, GA	5.388	11.564	1730.293	0.484	0.068
	(1.075)	(0.725)	(124.443)	(0.460)	0.404)
Total	7.310	14.066	1431.984	5.568	1.870
	(3.413)	(19.216)	(510.941)	(6.163)	(7.563)

Observations per U.S. county: 1561; Total observations: 71806.

Figure 1

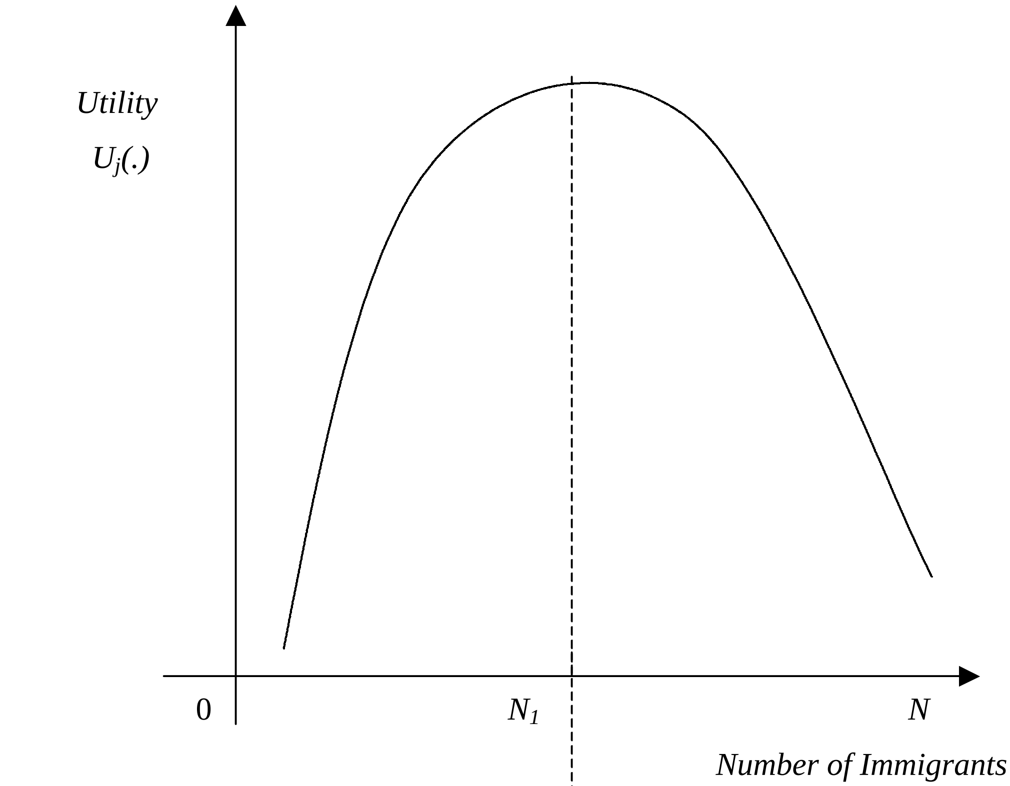


Figure 2

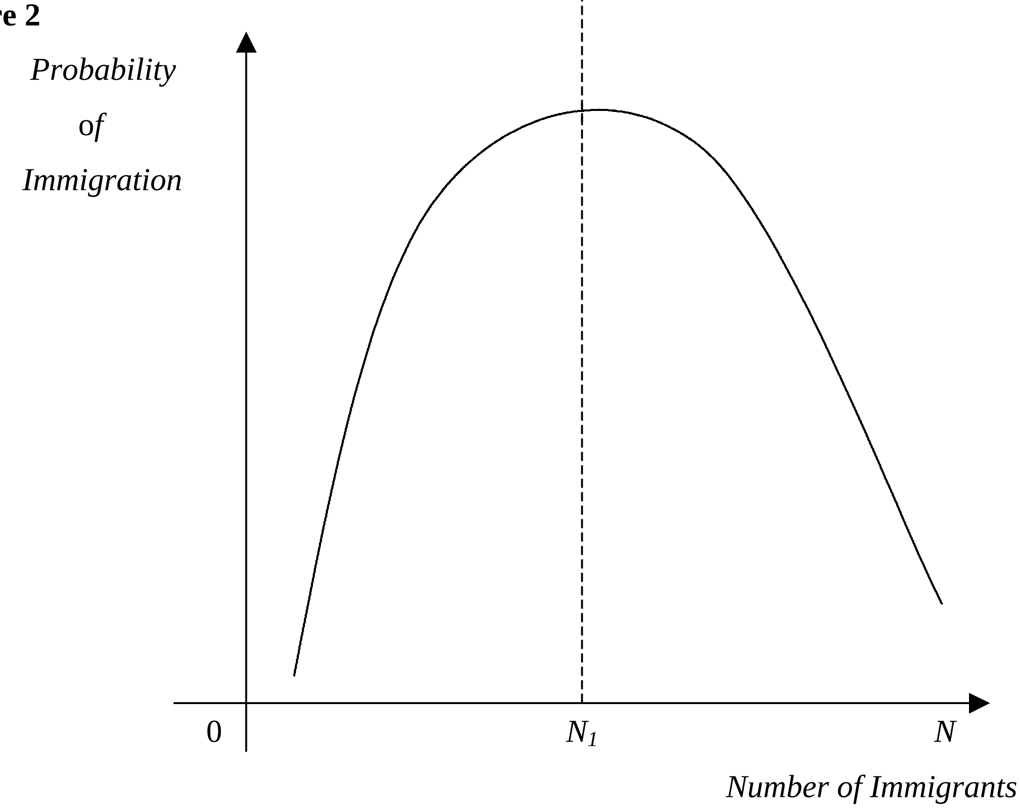


Figure 3

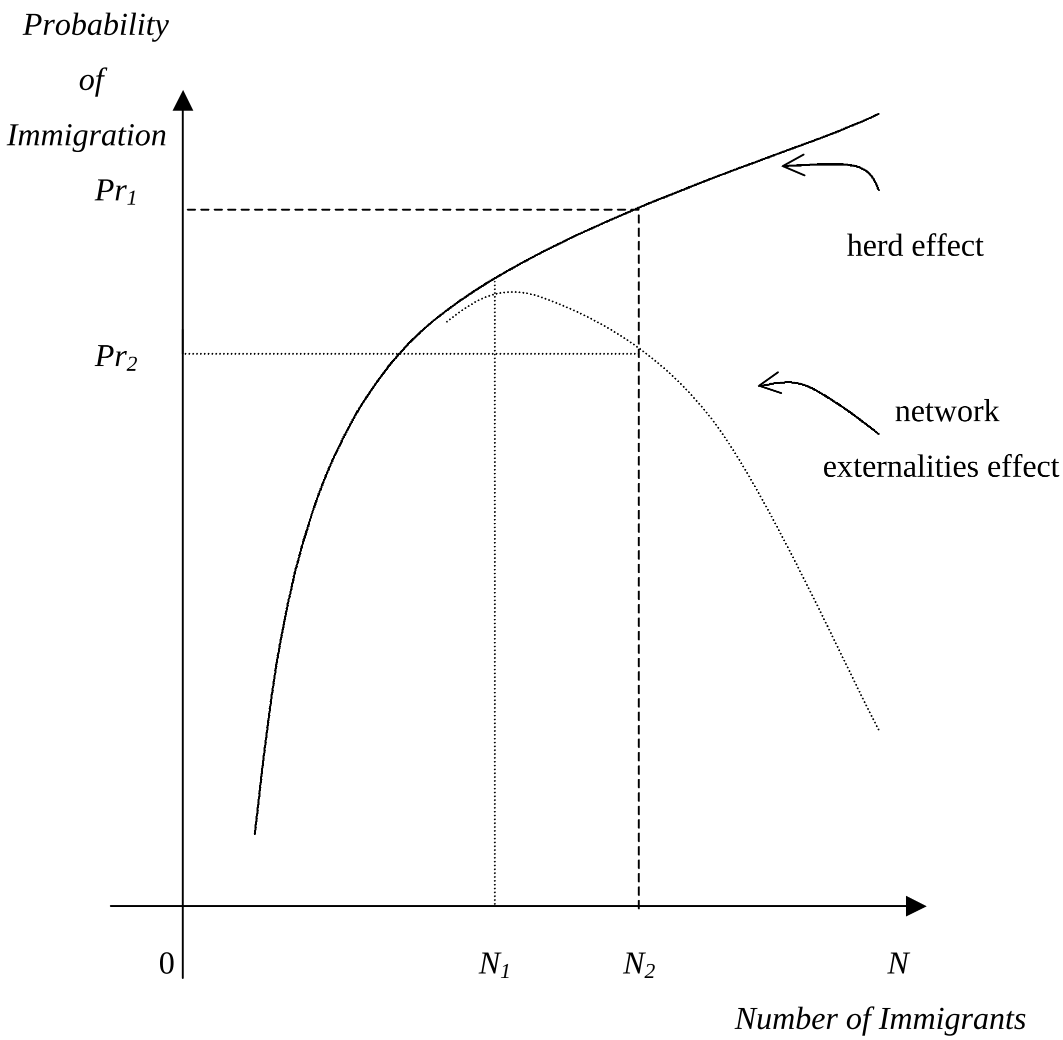

Probability
of
Immigration
Pr1
Pr2
herd effect
network
externalities effect
0
N1
N2
N
Number of Immigrants

Figure 4: Concentration of Mexican Migrants in the U.S.

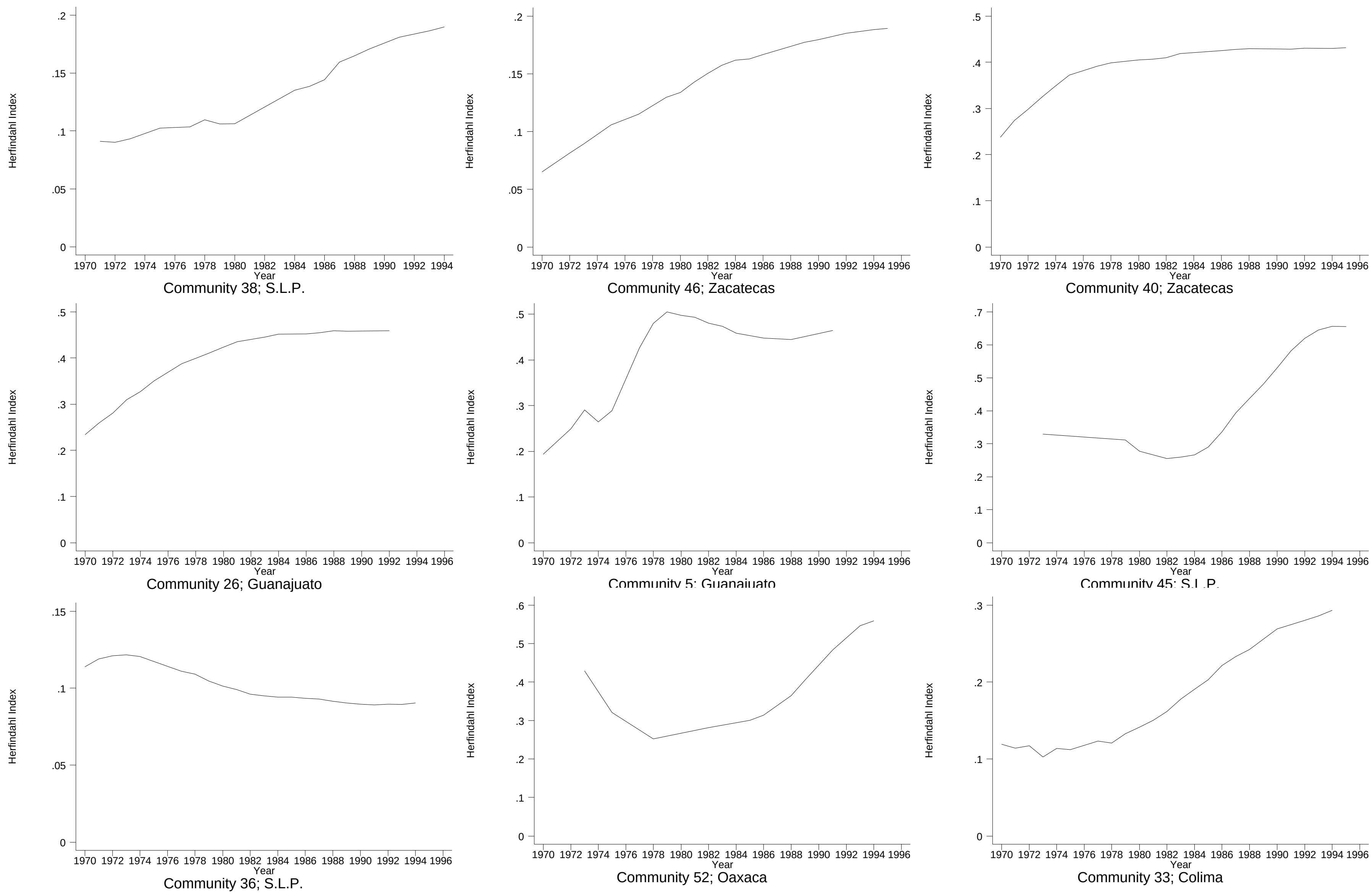


Figure 5:
Mexican Share of Population in Selected U.S. Locations

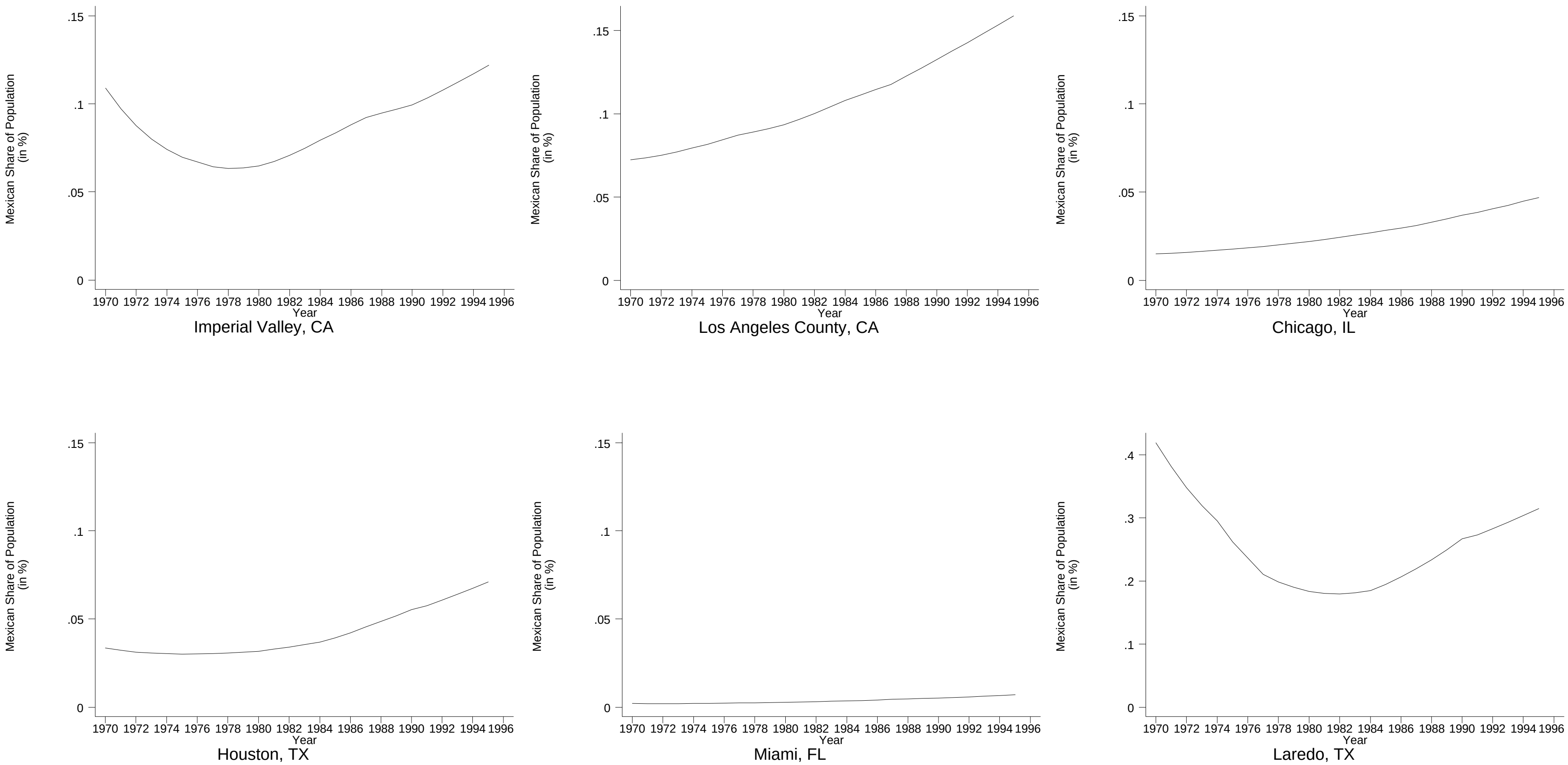
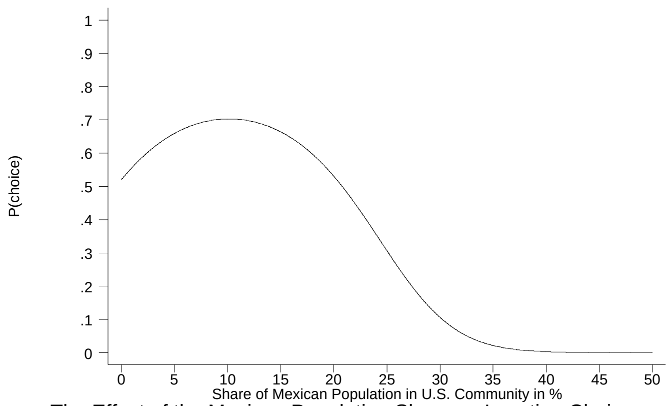


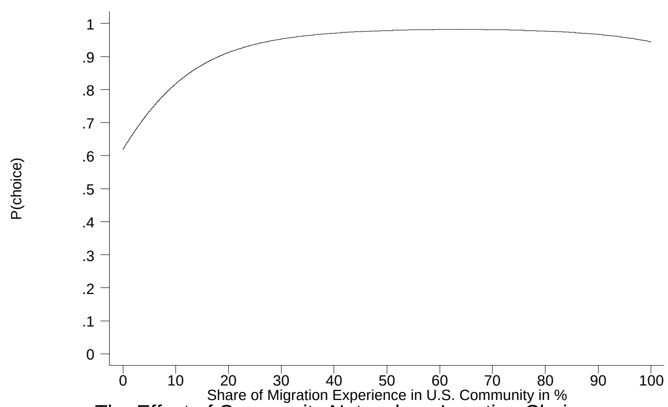
Figure 6:
Simulated Effects of Network and Herds: First Migration - Constrained Model

(a)



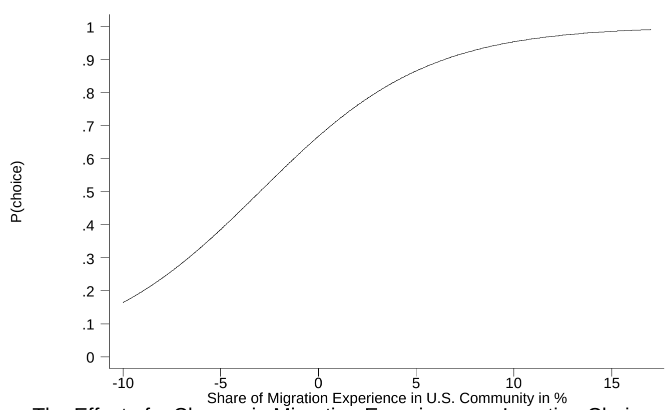
The Effect of the Mexican Population Share on Location Choice

(b)



The Effect of Community Network on Location Choice

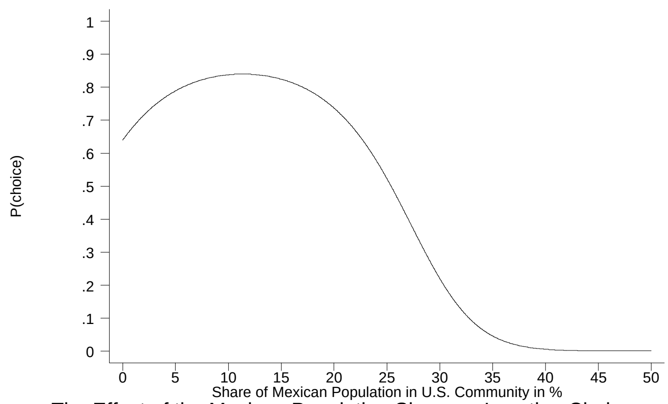
(c)



The Effect of a Change in Migration Experience on Location Choice

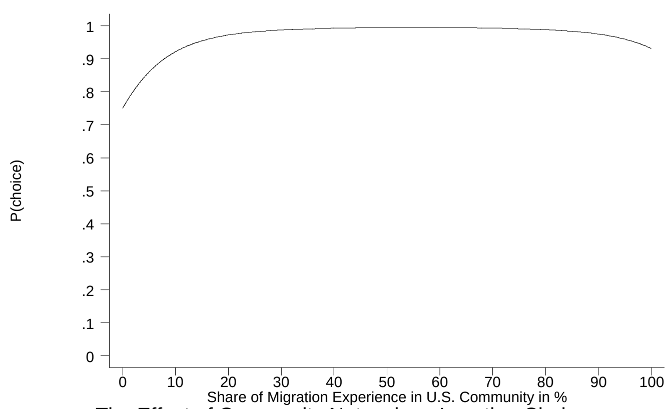
Figure 7:
Simulated Effects of Network and Herds: Last Migration - Constrained Model

(a)



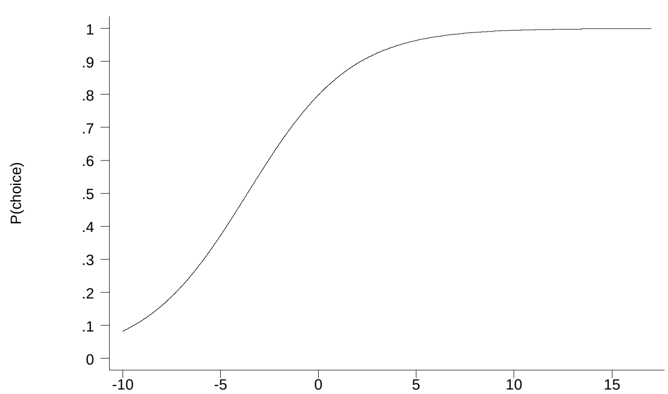
The Effect of the Mexican Population Share on Location Choice

(b)



The Effect of Community Network on Location Choice

(c)



The Effect of a Change in Migration Experience on Location Choice