Migrant Networks and the Spread of Misinformation*

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Abstract

Diaspora networks are a major source of information for future migrants. While the existing literature explains the effect of networks on migration decisions through the size of the migrant community, we show that the quality of the network is an equally important determinant of the timing and outcome of migration decisions. We argue that networks that are more integrated in the society of the host country can give more accurate information about job prospects to future migrants. In a decision model with imperfect signalling we show that migrants with access to a better network are more likely to make the right decision — they migrate only if they gain — and they migrate earlier. We test these predictions empirically using data on recent Mexican migrants to the US, and exploit the geographic diffusion of Mexicans since the 1970s to instrument for the quality of networks. The results give strong evidence that connections to a better-integrated network lead to better outcomes after migration. Yet we find no evidence that the quality of the network affects the timing of migration.

JEL codes: F22, J15, J61

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1 Introduction

It is well-established in the economics and sociology literature on social networks that communities differ in their ability to aggregate information and reach convergence in beliefs, depending on the social structure of the network (Granovetter, 1973, 2005; McPherson *et al.*, 2001; DiMaggio & Garip, 2012). In this paper we study how the ability of a community to aggregate information affects the success of the recipients of this information outside the community. We use as an example diaspora networks and the information they provide to potential migrants, and study how the social structure of these communities affects the success and the timing of the migration decision through the quality of information the communities are able to provide.

Prior to moving abroad, migrants face significant uncertainty about their job prospects abroad, which is why they often seek advice from diaspora networks. Not all these networks have the same knowledge about the labour market in the destination country; some networks are able to provide more accurate information than others. Following the literature on information diffusion in social networks, we argue that migrant communities that are well-integrated in the society of the host country have a greater knowledge of the labour market than ethnic enclaves, whose members typically have few interactions with the host society. Migrants with access to a well-integrated network receive more accurate information and are more likely to make the right decision; they migrate if they can expect to get a job that makes them better off, and they stay if they can expect a job that makes them worse off.

To fix ideas, we first explore the link between the information flows and the success of migrants in a 2-period decision model. Initially the migrant has some knowledge about his job prospects abroad, but not enough to convince him that migration will make him better off. He then receives information from the network and updates his beliefs of getting a good job. The more integrated the network, the lower the degree of misinformation, and the more likely the migrant is to make the right decision.

In a next step we develop this idea further, and study the effect of network quality on the timing of migration in a dynamic framework. In our model the migrant receives a signal from the network in every period, and faces the trade-off between migrating now under greater uncertainty, and postponing the migration decision and obtaining more information from the network. With every signal he updates his beliefs, and learns over time about his true odds of getting a good job abroad. The timing of migration is the solution of an optimal stopping problem; he emigrates once he has enough evidence that migration is beneficial. This threshold is reached earlier by migrants with access to a more integrated network, as every signal contains more accurate information.

We test the theoretical predictions using data on recent Mexican immigrants in the US. Mexicans have had a long tradition of emigrating to the US, but their settlement patterns have changed over time. Until the 1980s most Mexicans were concentrated in a few US states, while new arrivals since the 1990s have moved to a large number of places, which means that we can exploit a significant variation in the size and skill composition of Mexican communities across the US.

Key to the empirical analysis is measuring the quality of the network and the success of immigrants. For the quality of the network we use an assimilation index (Vigdor, 2008), which measures the degree of similarity between Mexicans and Americans in an area with respect to a wide range of characteristics. The choice of this proxy follows the observation in the literature on social networks that people with similar characteristics have more interaction. More interaction in turn leads to a more efficient aggregation of information, and more accurate information on job prospects that can be passed on to future migrants. To measure the success of migrants, we take the difference between wages of Mexicans in the US and in Mexico. As we cannot observe Mexicans in both countries at the same time, we predict counterfactual wages in Mexico based on observable characteristics. The larger the difference is between wages in Mexico and the US, the less successful is a migrant. We address potential concerns about the calculation of counterfactual wages using selection models, as well as different samples.

Identification of the effect of the network quality on the success and timing of recent migrants faces two challenges: reverse causality and omitted variables. Migrants with higher ability may choose to settle in places with more integrated networks, leading to a spurious positive correlation between the quality of the network and the success of a migrant. In addition, an omitted variable may drive both the quality of the network and the success of migrants. Larger networks, for example, may attract lower-ability immigrants and pay them a lower wage if they work within the community. If at the same time larger networks are less similar to Americans, network size would produce a spurious positive correlation between the quality of the network and the success of migrants.

To address these endogeneity issues we exploit the changes in the diffusion of Mexican communities throughout the United States. While until 1970 most Mexicans were concentrated in few metropolitan areas — most of them in Los Angeles, Chicago, and Houston/Dallas, immigrant communities settled in many other places throughout the US until the 1990s. With the diffusion of migrants, the concentration of Mexicans in small areas changed significantly. We instrument the assimilation of Mexicans in their local communities with the change in the concentration of Mexicans in the past, exploiting the fact that network characteristics were more persistent over time than the success of migrants within an area.

Our results confirm the first theoretical prediction. Migrants who moved to better integrated networks are more likely to be better-off compared to staying in Mexico. Yet the data do not confirm our second hypothesis that better networks lead to earlier migration. We discuss several possibilities why we cannot find an effect different from zero.

This paper contributes to five strands of the literature. First, it adds to the literature on aggregation and propagation of information in social networks. The theoretical literature has established that in social networks that are loosely connected information spreads faster (Jackson & Rogers, 2007), and false beliefs are less likely to stick (Acemoglu *et al.*, 2010; Golub & Jackson, 2010, 2012), because each member of a loosely connected group receives more information from members with many contacts outside the group. Alatas *et al.* (2012) confirm these predictions empirically at the micro-level for villages in Indonesia, showing that better-integrated networks are better at assessing the poverty status of all villagers. At the macro-level, Eagle *et al.* (2010) show that British communities with more connections to other communities have a higher GDP. Fogli & Veldkamp (2012) exploit the historical occurrence of infectious diseases to demonstrate a causal link between better-integrated networks and economic development. While all these papers show how the social structure of networks affects information flows, and ultimately outcomes, within a community, this paper illustrates how the ability of a community to aggregate information has an impact on members outside the community.

Second, it adds a new perspective to the literature on network effects in international migration. In large parts, the literature defines a network as the number of previous migrants in a given destination and studies how existing networks affect the decisions and outcomes of future migrants. One strand of this literature documents that migration is path-dependent; new migrants move to places where they find an established community from their home countries (Pedersen *et al.*, 2008; Beine *et al.*, 2010). Other papers argue that larger networks are associated with a negative selection of migrants. Larger networks decrease the moving costs, so that migration becomes profitable even for less-skilled workers (Carrington *et al.*, 1996; Winters *et al.*, 2001; Munshi, 2003; McKenzie & Rapoport, 2010; Beine *et al.*, 2011). As shown by Umblijs (2012), larger networks attract more risk averse migrants, while risk-loving migrants tend to move to smaller networks. This paper, by contrast, focuses on the *quality* of migrant networks as a driver of migration flows. The empirical results show that, in addition to the size of the network, its quality has an impact on the success of migrants.

Third, it adds to the growing literature on the role of information in migration decisions. As shown by Bertoli (2010), the selection of migrants can change significantly once there is uncertainty about wages abroad. This hypothesis is confirmed by McKenzie *et al.* (2013), who demonstrate that migrants have false beliefs about their employment and earnings prospects abroad. Based on a survey of Tongan migrants in New Zealand they show that prior to migration workers under-estimate both the chances of getting a job and the earnings possibilities. One explanation they offer is that migrant networks deliberately report lower earnings to their families at home to mitigate the pressure to send remittances. In a recent study, Batista & Narciso (2013) confirm the importance of the quality and frequency of information flows for the flow of remittances. They use a randomised control trial to increase the communication flows between immigrants and their networks abroad by providing calling credit to the treatment group. The authors provide evidence that increasing communication flows may promote higher remittances and more productive uses of remittances. Another important source of information is media. Farré & Fasani (2011) show for Indonesia that access to cable TV significantly reduces internal migration, because workers have more information about their potential destinations. Our paper, by contrast, shows that information not only shapes expectations and influences the decision to migrate, but also has an impact on the success of migrants.

Fourth, the paper also contributes to the literature on the impact of ethnic enclaves on the labour market outcomes of immigrants. Borjas (1995) shows that enclaves create human capital externalities that persist over generations. Children in ethnic enclaves grow up in the same closed-up environment, which leads to a persistence in skill differentials compared to people outside the enclave. Yet enclaves can also have a positive impact on the labour market outcomes of immigrants. Edin *et al.* (2003) find a large positive effect of ethnic concentration on the earnings of low-skilled immigrants in Sweden. As Andersson *et al.* (2009) show, the concentration of immigrants also increases the likelihood of getting a job for new immigrants. While these papers document the impact of networks on the outcomes of immigrants that have already emigrated, our paper shows that networks can even have an impact on migration decisions *before* emigration. Not only do migrant networks provide help in finding a job once a migrant has arrived, they also provide information to potential migrants in their home country.

Finally, the paper relates to the literature on the optimal timing of migration. This strand of the literature began with Burda (1995), who shows in a real options model that increased uncertainty about job prospects can lead to considerable delays in the migration decision. Moretto & Vergalli (2008) and Vergalli (2008) show in a similar framework that the timing of migration can be driven by networks that facilitate the integration abroad. Our dynamic decision framework builds on a similar methodology, but we explicitly model the relation between networks, information flows and the migration decision, which allows us to compare the success and the optimal time to migrate for networks with different degrees of integration.

The remainder of the paper is structured as follows. In Section 2 we motivate and extend our argument that more integrated networks provide more accurate information. We then illustrate the basic intuition in a simple decision model in Section 3.1. In Section 3.2 we generalise the findings from the simple model in a multi-period setting and present numerical examples. In Section 4 we test the theoretical predictions using data on Mexican migrants in the US. Section 5 concludes.

2 Migrant Networks as Providers of Information

Our basic argument is simple: migrant communities that are more integrated in the society of their host country are able to give better information to future migrants. Members of a more integrated community have a better knowledge of the labor market and can give future migrants more accurate information about job prospects. This argument is consistent with the *strength-of-weak-ties* hypothesis (Granovetter, 1973, 2005), which states that in many situations acquaintances – weak ties – are able to provide more important information than close family and friends – strong ties, because acquaintances have less overlap in their social contacts and receive information from outside one's own network. In contrast, close friends and family are more likely to have the same contacts and information sources, so that information easily becomes redundant.

Two examples for migrant networks with different degrees of integration are illustrated in Figure 1. The figure on the left describes an ethnic enclave. Its members, represented by the circles, have close connections within the network — strong ties, but very few connections to the outside world, represented by the crosses. An enclave is a typical example for a network with a high degree of closedness. This is a pervasive pattern in

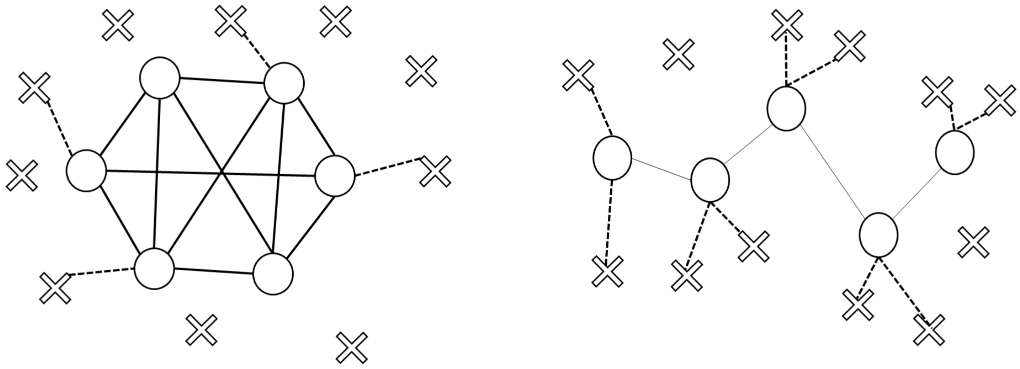

Figure 1 – Ethnic enclave (left) and loosely connected network (right)

Note: These two panels depict models of migrant networks. The circles represent the migrant network; the crosses represent information sources outside the network, i.e. native people or the media. The network on the left is an ethnic enclave, with strong connections within the network but weak connections to the outside world. The network on the right is a loosely connected migrant network, with strong connections to the outside world and weak connections within the network.

social networks, to which the literature often refers as *inbreeding homophily* — the fact that individuals with similar characteristics form close ties among each other (McPherson *et al.*, 2001; Currarini *et al.*, 2009). Examples for such closed-up migrant networks are Mexican neighbourhoods in Los Angeles or Chinatowns in most North American cities.

The graph on the right represents a well-integrated network, whose members have weak connections among each other but strong connections to the outside world. Examples for such groups are the Germans in London or the Dutch in New York.

There are two reasons why a potential migrant receives better information from a well-integrated network than from an enclave. First, the well-integrated network has more connections to the outside world. Its members receive more information and therefore have better knowledge about job perspectives in the receiving country. In contrast to this, members of an enclave typically have little knowledge of the language of the host country (Lazear, 1999; Bauer *et al.*, 2005; Beckhusen *et al.*, 2012). An enclave may offer job opportunities within the migrant community, but it has very limited information on the labor market outside the enclave.

Second, members of the well-integrated network only have weak ties among each other, so that misinformation — false beliefs about the world outside the network — is unlikely to persist. The members of an enclave, on the other hand, deal mostly with other members of the enclave. As shown by Acemoglu *et al.* (2010) and Bikchandani *et al.* (1992), misinformation is more likely to persist in such closely connected communities, as their members receive most of their information from each other.

To be certain, the two network formations in Figure 1 are polar cases that illustrate the differences between migrant networks, while in reality most networks will lie somewhere in between. In the theoretical analysis, we therefore introduce a parameter $\lambda \in [0, 1]$, which describes the ability of the network to aggregate accurate information.

3 Migrant Networks and Information: Theory

Having established that migrant networks differ in their ability to provide accurate information to future migrants, we now explain how the quality of information affects the outcome and timing of the migration decision. We first develop a two-period decision model and show that a migrant with access to a better network makes fewer mistakes in his migration decision. In Section 3.2 we extend the model to an infinite-horizon setting to study how networks affect the timing of migration.

3.1 Intuition from a Simple Model

We focus on the decision of a single worker, which allows us to isolate the effect of a large network on one migrant from feedback effects that may arise if a whole group of people emigrates.[1] We also assume that networks already exist and that their quality is constant over time.

Consider a potential migrant whose job at home that gives a lifetime income of $\underline{w} = 0$. If he moves abroad he can either get a good job that pays him a discounted lifetime income of $w^G > 0$ or a bad job that pays $w^B < 0$. Before he emigrates it is uncertain which job he will actually get. If he migrates, he has to pay a sunk moving cost M. We assume that $w^G > M$; otherwise migration would never be beneficial. For simplicity, we assume that he is risk-neutral. He migrates if his expected income from migration minus the moving costs is greater than his income at home,

$$\mathbb{E}(U(k)) = p(k)w^G + (1 - p(k))w^B - M \geq 0, \tag{1}$$

where $p(k)$ is the belief probability — the belief that he gets a good job abroad — which depends on his level of information k. Initially, his best guess is a commonly known probability p_0. For example, p_0 could be the fraction of previous migrants that got a

[1] See Epstein (2010) for a model of informational cascades within a group of migrants.

good job. If he receives information from the network he will learn more about his actual odds of getting a good job, so that his best guess changes from p_0 to some other $p(k)$.

Figure 2 illustrates the worker's decision problem. In the first period t=1 he can decide whether to emigrate or stay. If he stays, he earns his wage at home, and he obtains additional information from the network in the second period. The signals from the network can be of two types,

g: he will get a good job after migration
b: he will get a bad job after migration.

A positive signal g brings him to information set $2A$, at which he knows that he has received a positive signal, but he does not know whether he is at the upper node — and he actually gets a good job — or at the lower node. A negative signal b brings him to the information set $2B$. Based on the signal he updates his beliefs from p_0 to $p(k)$, with

$$k = \begin{cases} 1 & \text{if he receives a positive signal } g \\ -1 & \text{if he receives a negative signal } b \end{cases}$$

A positive signal increases his belief probability, while a negative signal decreases it, so that $p(1) > p_0 > p(-1)$. The signal is truthful with probability λ, which is a function of the network quality. The more integrated the network, the higher is λ and the more accurate is the information. We assume that networks provide information to the best of their knowledge, which means that we abstract from networks spreading misinformation deliberately. Networks provide noisy information about job opportunities because they do not know any better.

If the migrant gets a good job abroad, then the signal is positive with probability λ and negative with probability $1 - \lambda$. The opposite holds if he gets a bad job. Following our argument from Section 2, a network with more knowledge about the labour market sends a more truthful signal and spreads less misinformation. As it is unrealistic that a network has perfect knowledge and completely eliminates the migrant's uncertainty, we assume that $\lambda < 1$. At the same time, λ has to be greater than $\frac{1}{2}$ for the signal to convey a minimum level of truthfulness.[2]

We assume that only $p(1)$ fulfills Equation (1), so that the worker only migrates if he has received a positive signal. In the second period only two actions lead to correct decisions. In the upper node of information set $2A$ he has received a positive signal, in

[2] Otherwise, the signal would either be completely noisy ($\lambda = \frac{1}{2}$) or it would indicate the opposite of the true state of the world ($\lambda < \frac{1}{2}$).

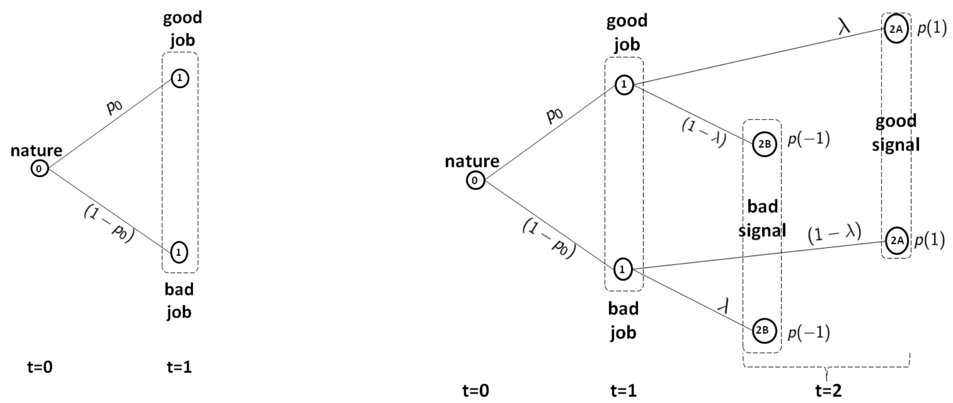

FIGURE 2 – DECISION TREE FOR A POTENTIAL MIGRANT: FIRST STAGE (LEFT), SECOND STAGE(RIGHT)

Note: Decision tree with 2 stages. The panel on the left shows the first stage only, the panel on the right shows both first and second stage. In the first stage the migrant only knows the a-priori odds of getting a good job, p_0. In the second stage he receives a signal from the network which is truthful with probability λ. He migrates if the signal is positive and he stays if the signal is negative.

which case he migrates and gets a good job; in the lower node of information set $2B$, he has received a negative signal, so he stays while he would get a bad job if he emigrated. The remaining two actions lead to a wrong decision — a decision that makes him worse-off than he would otherwise be. In the lower node of $2A$ he migrates despite getting a bad job abroad, while in the upper node of $2B$ he stays although he could gain from migration. Table 1 summarises the probability distribution for the terminal nodes on the decision tree.

TABLE 1 – PROBABILITY DISTRIBUTION OF TERMINAL NODES

	Job	**Signal**	**Action**	**Probability**	**Decision**
1)	Good	Positive	Migrate	$p_0\lambda$	correct
2)	Good	Negative	Stay	$p_0(1-\lambda)$	*wrong*
3)	Bad	Positive	Migrate	$(1-p_0)(1-\lambda)$	*wrong*
4)	Bad	Negative	Stay	$(1-p_0)\lambda$	correct

Clearly, the probability of making the wrong decision (rows 2 and 3 in Table 1) decreases with the signal quality λ. The higher λ, the lower is the spread of misinformation.

Proposition. 1 *A potential migrant with access to a better network is less likely to make errors in his decision to migrate. He is more likely to stay when his prospects abroad are bad and more likely to migrate if his prospects abroad are good.*

The person only emigrates if he has enough evidence that emigration is beneficial — that is, if the number of positive signals k is at least as great as some threshold value, $k > k^*$. For simplicity we have assumed so far that one positive signal is sufficient. The result from Proposition 1, however, does not hinge on this assumption.[3]

The aim of this model is to fix ideas, and to provide testable hypotheses, using the simplest possible framework. The model can certainly be enriched along a number of dimensions, which we discuss in the following. First, we assume that the migrant is risk-neutral, so that his decision is based on expected income. It would be possible to model the objective function as a quasi-concave utility function which allows for risk-aversion. While such a function would potentially be more realistic, it would leave the qualitative results in Table 1; more risk-averse migrants would simply require a larger number of positive signals, but Proposition 1 would still hold.

Also, the objective function does not consider changes in reference points. In our model the migrant compares the expected income in both countries, without deriving utility from a comparison with a reference group. A change in reference points — for example from the average wage in the country of origin to the average wage in the destination, may create some disutility which lowers the gains from migration (Akay *et al.*, 2012). As with risk-aversion, the change in reference points would change the threshold number of signals, but not the error probabilites.

3.2 Networks and the Timing of Migration

Next, we extend the simple framework to a multi-period model in discrete time, which allows us to study the effect of the quality of the network on the timing of migration.[4]

The setting is the same as in the 2-period model. The migrant receives a signal from the network in every period and learns over time about his true job prospects. In every period he faces a trade-off between migrating now and waiting for the next signal. He has to weigh the cost of uncertainty today against the opportunity cost of waiting for the next signal. If he migrated today he could reap the potential benefits of migration immediately, but he would also face a higher uncertainty. If he waits one more period he learns more about his prospects, but he can only benefit from migration in the next period. We model this trade-off as an optimal stopping problem, in which the potential migrant accumulates

[3] It is possible to extend the model from two periods to an infinite horizon, and to express the threshold k^* as a function of wages, moving costs, the discount factor, and the prior probability. As shown by Thijssen *et al.* (2004), Proposition 1 still holds in such a more general setting.

[4] The general framework in this section follows Thijssen *et al.* (2004) and Delaney & Thijssen (2011).

information and postpones the migration decision until he has sufficient evidence that he will get a good job. The sufficient amount of information depends on several parameters: the wages for good and bad jobs, moving costs, the discount factor, and the initial belief of obtaining a good job.

The number of good signals $g(t)$ evolves according to the law of motion $dg(t) = udt$, with $g(0) = 0$ and

$$u = \begin{cases} 1 & \text{with probability } \lambda \text{ if } w^G \text{ and } (1-\lambda) \text{ if } w^B \\ 0 & \text{with probability } \lambda \text{ if } w^B \text{ and } (1-\lambda) \text{ if } w^G \end{cases}$$

Initially the potential migrant has a prior belief p_0. With every signal he learns more about his prospects and updates his beliefs by making a best guess given the available information. If he has received n signals in total, of which g were good, his belief probability according to Bayes' rule is,

$$\begin{aligned} p(n,g) &= \frac{\mathbb{P}(n,g|G)\mathbb{P}(G)}{\mathbb{P}(n,g|G)\mathbb{P}(G) + \mathbb{P}(n,g|B)\mathbb{P}(B)} \\ &= \frac{\lambda^k}{\lambda^k + \frac{1-p_0}{p_0}(1-\lambda)^k} \equiv p(k), \end{aligned} \tag{2}$$

where $P(G) = p_0$ and $P(B) = 1 - p_0$ are the unconditional probabilities of getting a good or a bad job. We define $k := 2g - n$ as the excess number of good signals to bad signals.[5] At a threshold k^* the expected gain from migration in Equation (1) equals zero, so that the worker is indifferent between migrating and staying. The corresponding belief probability is $p^* = p(k^*)$. If the number of signals and the belief probability exceed k^* and p^*, the migrant will have a higher expected income abroad, and hence emigrates. If both values are below the threshold, the migrant is better-off waiting for the next signal. Starting at time $t = 0$ he will keep the option to migrate open until the number of positive signals exceeds k^*. Solving Equation (2) for k and evaluating at $p^* = p(k^*)$, we obtain the threshold number of positive signals,

$$k^* = \frac{\log\left(\frac{p^*}{1-p^*}\right) + \log\left(\frac{1-p_0}{p_0}\right)}{\log\left(\frac{\lambda}{1-\lambda}\right)}. \tag{3}$$

The unique solution for k^* can be obtained from dynamic programming. Formally

[5] He receives n signals, of which g are good and $n - g$ are bad. The difference between good and bad signals is $g - (n - g) = 2g - n$.

deriving the solution is mathematically demanding, as k^* depends on p^*, which in turn is a function of several parameters, $p^* = p(\lambda, r, w^G, w^B, M)$. To demonstrate the mechanics of the model we present a simple numerical example and refer the interested reader to the Appendix A.1 for a formal derivation of k^* and p^*. We calibrate the model on the parameters listed in Table 2 and vary the quality of the network λ. After emigration the worker can either gain 20,000 or lose 10,000 compared to his job at home. The fixed moving costs are 10,000. He knows that on average 60% of all emigrants get a good job. The parameter values only serve illustrative purposes, but as we show in the comparative statics below, the qualitative results hold for a wide range of parameters.

Table 2 – Parameters for the simulations

w^G	20,000	gain in discounted life-time income after getting a good job
w^B	-10,000	loss in discounted life-time income after getting a bad job
M	10,000	sunk moving cost
p^0	0.6	unconditional probability of getting a good job
r	0.1	discount rate
λ	0.75	probability of a truthful signal

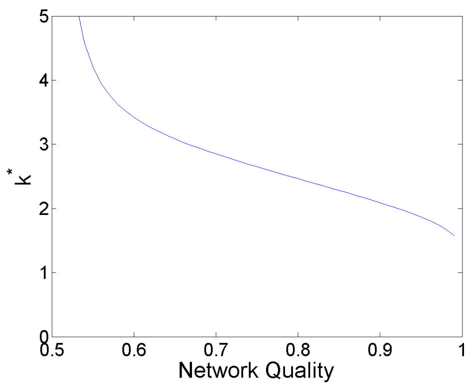

Figure 3 – Comparative statics: change in the network quality λ.

Notes: The threshold belief probability p^* increases with the network quality λ. With a higher network quality a potential migrant demands more certainty about his prospects. Right: the threshold number of positive signals k^* decreases with the network quality λ. A better network reduces the uncertainty of migration and the potential migrant requires less positive information to emigrate.

As we can see in Figure 3, a better network requires a lower number of positive signals. If the signal is truthful with a probability of 55% he requires 4 positive signals in excess of negative signals, while he only requires 2 positive signals if the signal is truthful with 95%. This leads us to the following proposition:

Proposition. 2 *A potential migrant who receives signals from a high quality network emigrates earlier.*

Signals with a higher quality reduce the uncertainty more than low-quality signals. A migrant with access to a good network requires a lower number of positive signals to have sufficient evidence that emigration is beneficial.

Figure 4 shows how the threshold number of positive signals is related to other parameters. Changes in wages for good and bad jobs, w^G and w^B, as well as the moving costs M work through the expected income channel. An increase in the gains from a good job, a decrease in the losses from a bad job, or a decrease in the moving costs increase the expected gains from emigration, so that a lower number of positive signals is sufficient. The negative relation between k^* and the discount rate r is intuitive. A low discount factor puts more weight on income in the future and leads to low opportunity costs of waiting, in which case a worker needs many positive signals to convince him to migrate early. Finally, k^* decreases in the prior probability p_0. If a worker knows that the majority of migrants get a good job, he does not require many positive signals to be convinced.

From the model we hypothesise that the higher the probability of misinformation, the later a potential emigrant migrates.

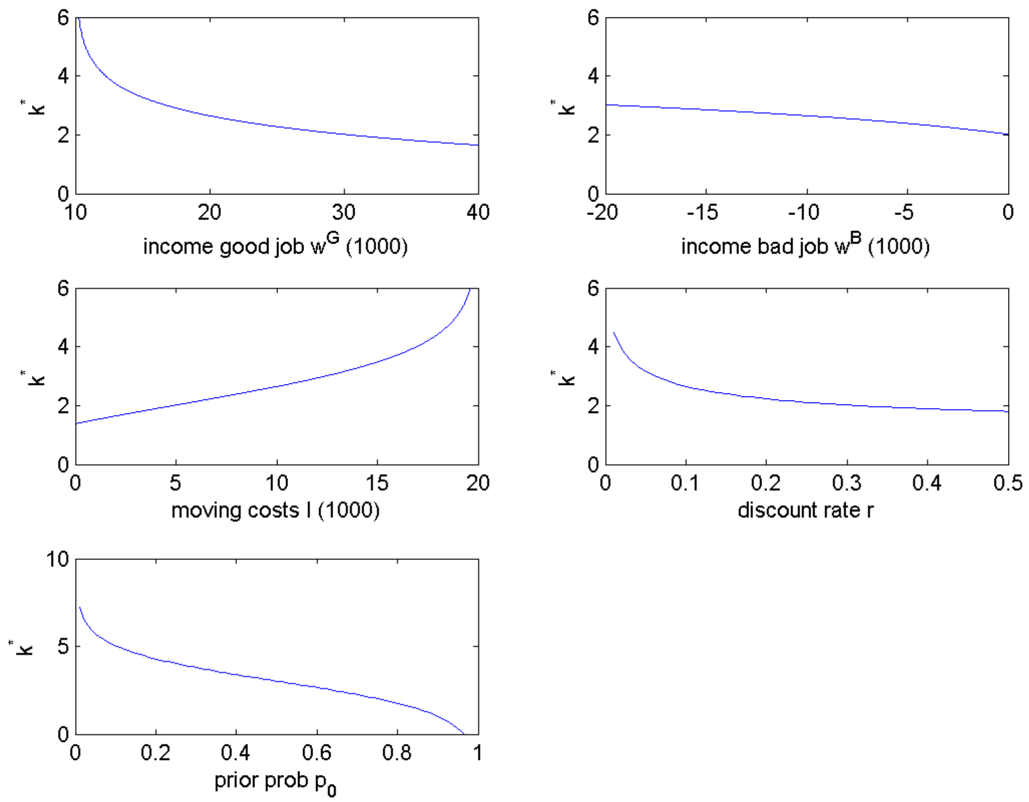

FIGURE 4 – COMPARATIVE STATICS: VARIATION IN THE MODEL PARAMETERS

Notes: The graphs show the changes in the threshold number of positive signals k^* subject to a change in the key parameters. In each graph, the other parameters are held constant at the values stated in Table 2.

4 Empirical Investigation

4.1 Empirical Strategy

We now turn to the empirical test of the theoretical predictions. The aim of this exercise is to present empirical patterns that are consistent with the theoretical predictions, and to explore the channels through which networks affect migration decisions. While previous literature concentrates on the size of the network as the main driver of migration flows, we want to see if the quality of the network also has an impact on the migration outcome and the timing of migration.

The testable hypotheses are that migrants with access to a better network 1) are less likely to migrate if they actually get a bad job abroad, 2) are less likely to stay if they would get a good job abroad, 3) they migrate earlier, given migration is beneficial for them. In a linear specification, the hypotheses translate into the equation

$$y = \alpha + \beta \text{network} + \boldsymbol{X'}\boldsymbol{\gamma} + \varepsilon, \tag{4}$$

in which the outcome of interest y — the probability of making an error in the migration decision, or the timing of migration — is explained by the network quality, individual characteristics $\boldsymbol{X}$, and factors that are unobservable to the econometrician.

In the following, we will test the first and third hypotheses, as both can be tested with data on actual migrants from the receiving countries. The second hypothesis is more difficult to test, as it requires information on workers that stay at home but that would actually gain from migration. In most poor and middle-income countries there are millions of workers who would gain from migration, but only a fraction actually has the intention to emigrate, so that it is hardly possible to spot potential migrants in a source country.

We use data on Mexican immigrants in the US, for which we can observe the characteristics of a large number of communities across the entire US. Mexicans have had a long tradition of emigrating to the US, which led to well-established Mexican networks in many US cities. Yet the settlement pattern has changed in the 1990s. While until the 1980s most Mexicans went to California, Texas, and Chicago, many Mexicans in the 1990s settled in areas that had no significant Mexican community before, such as Atlanta, Denver, Raleigh-Durham, Seattle, or Washington, D.C. (Card & Lewis, 2007). This gradual diffusion of Mexicans across the US means that we can exploit a significant degree of variation in network characteristics across metropolitan areas and over time, and link them to the outcomes of recently arrived immigrants. Another advantage of looking at one nationality is that it reduces unobserved heterogeneity between source countries, as the network characteristics and the success of migrants probably differ less within a nationality than between different nationalities.

The estimation of Equation (4) faces two important challenges: measurement and identification. Measurement of the outcome of interest and the quality of the network is not straightforward; both variables need to be defined first. While it is possible, for example, to compute the size of the network from the number of Mexicans in a given geographic area, it is less straightforward to define factors that describe the quality of the network. Determining the potential error a migrant makes is equally challenging because of the absence of a counterfactual. As we can only observe a person either in Mexico or in the US but never in both at the same time, we cannot directly compare their situation in both countries. To measure the quality of the network we use an assimilation index, which measures how similar Mexicans and Americans are within an area. The choice of the assimilation index as a proxy for the integration of a network follows from the well-established fact in the literature on social networks that communities with similar characteristics are more likely to interact with each other. In our case, this means that Mexican communities that are more assimilated, are also more likely to interact with Americans, and therefore have a better knowledge about the labor market in their area, which they can pass on to future migrants. We also address the problem of a missing counterfactual by predicting counterfactual wages — the wages a migrant would have earned had he stayed in Mexico — based on observable characteristics. To tackle the potential selection problems in estimating the counterfactual wage, we provide several estimates based on selection models and a matched sample.

Another important challenge is identification of the effect of networks on migration outcomes, which faces at least two threats. First, unobserved factors may determine the characteristics of the network and the outcome of interest, and thus bias the estimates of a simple regression of the outcome of interest on the network quality. A second factor is omitted variables. There may be many determinants of migration outcomes besides networks, and it is not sure whether we can control for all these factors so that the remaining variation only comes from networks. To overcome these empirical problems we rely on an instrumental variable strategy, in which we exploit past changes in the geographic concentration of Mexicans. These are a significant predictor of the assimilation of a network. At the same time, we show that there is little persistence in the success of migrants settling in a given area over time, which corroborates the exclusion restriction.

In this section we first describe the data sources and the characteristics of the sample. We then discuss in detail the measurement of the key variables and the IV strategy before we present and discuss the results.

4.2 Data and Descriptive Statistics

4.2.1 Datasets

The core datasets used in the regressions are the 2000 US census and the 2010 5-year file of the American Community Survey (ACS). For the calculation of counterfactual wages we also use the Mexican census of the years 1990, 2000, and 2010, and we use the US census of the years 1980, 1990 and 2000 to compute an index for the network quality and the instrumental variables.

The US census is conducted every year and includes the entire population. We use the 5%-samples provided by IPUMS.[6] As the census data of 2010 has not been released yet, we have to rely on the ACS. The 2010 5-year file is similar to census in terms of variables, number of observations, and representativeness. It combines the 1%-ACS files for the years 2005-2009. To make incomes comparable over the 5 years, they are adjusted to 2009 prices. The 2000 and 2010 rounds have a large number of observations, which ensures that the sample is representative even if we restrict our analysis to recent Mexican immigrants, which are a very small subpopulation. Furthermore, a Mexican census is available for the same years, so that we can match the information from the US census with wages in Mexico. We do not use earlier census rounds for the regressions, as our identification relies on historical variables, which we can only compute from 1980 onwards. Both the US census and the ACS are representative at the individual and the household level. It contains rich information on individual and household characteristics. Important for our analysis is information about the age at the time of immigration, birth place, current employment, education, and family situation.[7]

Besides the advantages mentioned above, the US census has two important limitations: it has no direct information on the network of the migrant, and the information flows between the network and the migrant prior to migration. Other datasets, for example the Mexican Migration Project, contain some information on the help of friends and family members in the migration decision. However, these datasets do not contain information on the network that goes beyond family and friends, and have limited variation in networks across destinations. Another limitation of the census data is that it has no information on wages prior to migration. These would be helpful to compare the migrants' situation in Mexico and the US.[8]

The sample consists of Mexican immigrant men who arrived in the US no longer than 5 years before the census. We define immigrants as Mexican citizens who were born in Mexico and report in the census that they were residing in Mexico 5 years ago. The sample is restricted to Mexicans aged 18-64 who were at least 18 years old when they

6 Ipums: Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

7 The census includes both legal and illegal migrants, although it does not flag them as illegal migrants. Moreover, the census only includes people that stay in the US long-term; it does not include people that are on a tourist visa, or any other short-term visitors (Hanson, 2006).

8 See Appendix B for other datasets on Mexicans in the US.

moved to the US, and who moved to a district with at least 20 Mexicans.[9] An outline of further restrictions to the sample can be found in Appendix C.

The restriction of the sample to recent migrants is the result of a trade-off between having a measure of lifetime success on the one hand, and having accurate information on the network and a less selective sample on the other hand. The gold standard for measuring the success of migrants would be to compare their lifetime earnings in the US with counterfactual lifetime earnings in Mexico. Unfortunately, detailed data on the entire earnings history of migrants is not available. If we used information on migrants that have been in the US for a long time from a single census round, we would not be able to reconstruct a migrant's network at the time of arrival. Moreover, as shown by Biavaschi (2012) and Campos-Vazquez & Lara (2012), selective out-migration of more successful migrants would lead to an under-estimation of the success of migrants. With the focus on recent migrants we can only measure their short-term success, but we can obtain a more precise measure of their network, and the sample is less selective.

A potential problem regarding sample selection is the misreporting of the date of entry. Transient migrants — those who move back-and-forth between Mexico and the US — tend to report the date of their last arrival in the US, even though they had a longer history of migration to the US (Redstone & Massey, 2004; Lubotsky, 2007). [10] To reduce the bias from misreporting the year of entry, we only include migrants who state that they lived in Mexico 5 years ago.

Another concern with data on Mexicans in the US is the undercounting of illegal migrants. The majority of Mexicans in the United States arrive as illegal immigrants and only receive their residence permit at a later stage (Massey & Malone, 2002; Hanson, 2006). The census does not ask respondents about their legal status. Yet some illegal migrants may fear negative consequences and choose not to take part in the survey, or they may not be available for some other reason. The undercount of illegal migrants can lead to selection bias, if the least-skilled migrants are more likely to be excluded. While we are aware that undercounting may bias the results, it is important to note that the extent of undercounting has decreased significantly over the last census rounds, from 40% undercount rate in 1980 (Borjas *et al.*, 1991) and 15-20% in the 1990s (Bean *et al.*, 2001; Costanzo *et al.*, 2002), to around 10% in the 2000 survey (Card & Lewis, 2007). Moreover, Chiquiar & Hanson (2005) show that undercounting only causes minor changes

9 As districts we use consistent PUMAs (public use microdata area).

10 One reason for the misreporting among transient migrants is the ambiguous wording of the census question. In 1990 it asked when the person "came to stay", in 2000 the question was when they "came to live" (Redstone & Massey, 2004).

to the wage distribution of Mexicans in the US, which means that there is no systematic undercount of a particular skill level.

4.2.2 Measuring the Success of Migrants

Next we turn to the construction of the dependent variable. Following the theory, we require a measure for an error in the migration decision — that is, a variable that indicates if a person would be better off in Mexico than in the US. For measuring the error, we use the difference between wages in Mexico and in the US. The larger the value of this difference, the higher is the wage in Mexico relative to the US, and the more likely it is that an immigrant is actually worse-off in the US. While the wage difference may not be as precise in measuring the error as a binary variable — 1 if the wage in Mexico is larger, and 0 otherwise — it allows us to use a linear econometric model and instrumental variables.

To calculate the wage difference, we would ideally require information on earnings of the same person in the US and in Mexico. This creates a challenge for measurement, as we can neither observe the same worker in two countries at the same time, nor is the census a longitudinal dataset that contains information on wages before emigration. To obtain a Mexican wage nontheless, we predict a counterfactual wage based on observable characteristics. We attribute to every worker in the US the wage of an average Mexican worker with similar characteristics. The counterfactual wages can obviously differ from the actual wages, for example if there is selection into migration, so that there are unobservable characteristics that make migrants and stayers different from each other. We discuss the potential of selection bias in light of the recent literature on the selection of Mexicans in the US, and corroborate our predictions with a number of robustness checks.

From both the Mexican and the US census we use monthly wage data to calculate the wage difference. As Mexicans in the US and Mexico may differ in the number of working hours, we adjust wages by the number of working hours in a typical work week, and the number of weeks worked in a typical year. In addition, we convert Mexican wages into US dollars and account for differences in price levels using a PPP factor.[11] Initially we only include workers with a positive income in the wage regressions. Later on, we test the robustness of the wage predictions using a 2-step selection model on the full sample.

To predict the counterfactual wages, we proceed as follows. We first use the Mexican census to regress monthly wages on a vector of personal characteristics,

[11] See Appendix C for a description of the samples and the wage adjustment.

$$\text{wage} = \boldsymbol{X_{MEX}}\boldsymbol{\beta_{MEX}} + \varepsilon, \tag{5}$$

to obtain an estimate for skill prices in Mexico, $\hat{\boldsymbol{\beta}}_{\boldsymbol{MEX}}$. $\boldsymbol{X_{MEX}}$ includes a set of education dummies, a dummy for marital status, age, and age squared, as well as interactions of the education dummies with the dummy for marital status, age, and age squared. ε is an error term that captures unobservable determinants of wages. The interaction terms allow us to have a separate age-earnings gradient for each education level. Because the coefficients may differ significantly by gender, we run separate regressions for men and women.

Using the same characteristics for Mexicans in the US, $\boldsymbol{X_{US}}$, we predict the counterfactual wages as

$$\widehat{\text{wage}} = \boldsymbol{X_{US}}\hat{\boldsymbol{\beta}}_{\boldsymbol{MEX}}. \tag{6}$$

The difference between the counterfactual and the actual wages yields what we call losses from emigration. Figure 5 shows the distribution of the losses from emigration for Mexicans with a positive wage income in the US. As we can see, most Mexican workers in the US are financially better off than in Mexico. The average Mexican in 2000, conditional on working, earns around 1000 USD per month more in the US. In 2010 the average difference is even 1400 USD. Yet in both years around 5% of the distribution would be better off in Mexico, and around 25% have a wage difference of less than 500 USD. If we include those in the US without income, the share of workers with a positive wage difference increases considerably.

Due to unobserved factors we potentially over- or under-estimate the counterfactual wages. The prediction of counterfactual wages in Equation (6) assigns to every Mexican in the US the average wage of a worker in Mexico with the same observable characteristics. But education, age, gender, and marital status only capture some of the factors that determine wages. Unobserved factors, such as IQ, confidence, motivation, or self-selection into a certain type of firm potentially have a large impact on wages and can explain wage differentials between workers with identical observable characteristics. If migrants are positively selected — that is, if they are on average more skilled than comparable workers in Mexico — we under-estimate the counterfactual wages and undercount the number of workers who would be better off in Mexico. If migrants are negatively selected, we over-estimate the counterfactual wages and the losses from emigration.

The literature on the selection of Mexican migrants has not reached a consensus on the

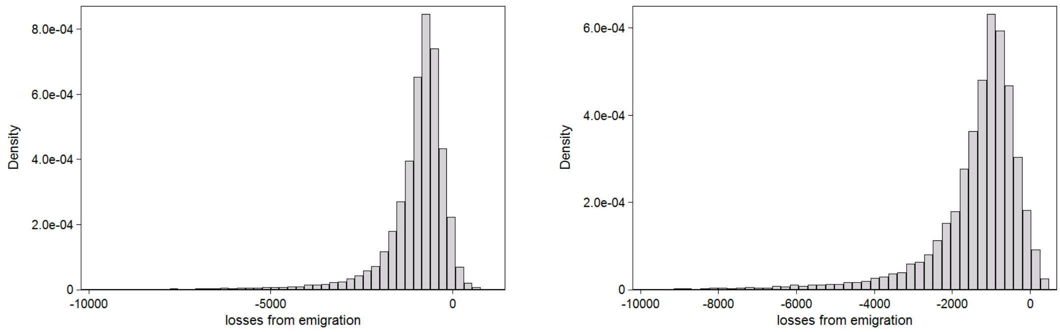

FIGURE 5 – LOSSES FROM EMIGRATION, 2000 AND 2010

Note: The graphs show the distribution of the losses from emigration in 2000 and 2010, which are measured as the difference between the counterfactual and the actual annual income. A Mexican in the US has positive losses from emigration if, based on his observable characteristics, he would have a higher income in Mexico than in the US. The graphs only include workers with a positive income in the US. Data sources: Mexican census, US census, and ACS.

direction of selection bias. Chiquiar & Hanson (2005) and Orrenius & Zavodny (2005) and Kaestner & Malamud (2013) find that the selection of Mexican migrants occurs mostly at the center of the wage distribution. This view has been challenged by Ibarraran & Lubotsky (2007), Fernández-Huertas Moraga (2011) and Ambrosini & Peri (2012), who use longitudinal data to show that Mexican migrants are negatively selected from the wage distribution, in which case we would over-estimate the losses from emigration and classify too many immigrants as being better off in Mexico. Fernández-Huertas Moraga (2013) demonstrates that the selection pattern depends on the migrants' location in Mexico. He finds that Mexicans moving from urban areas are positively selected, while those from rural areas are negatively selected.

While our cross-sectional data does not allow us to analyze directly the direction and magnitude of the selection bias, we can get an idea of its importance by using different samples and econometric techniques for the prediction of counterfactual wages. In total, we use three different approaches. If we cannot directly observe counterfactual wages, the second best is to predict them based on Mexicans that are as similar as possible to Mexicans in the US. We first use a sample of Mexicans that are matched to similar migrants based on observable characteristics (age, gender, number of children, education). Based on a probit model we estimate for every Mexican in the initial sample the propensity of being a migrant, and only include observations in the sample whose propensity score is above the median. In another approach we restrict the sample to internal migrants, as these are more mobile and may be more similar to Mexicans in the

US than the average person in the census. The third approach accounts for selection into migration, as well as for selection into employment in Mexico. The baseline predictions only include Mexicans with positive income, which can be an additional source of bias. Using the matched sample, we estimate a two-step Heckman model, with the number of children as exclusion restriction.

Another potential source of bias is the misreporting of educational attainment. Education is self-reported in the census, and although respondents do not benefit from misreporting, there is evidence that migrants over-report their education level (Lubotsky, 2007), for example to make them look better in front of the interviewer or other people present at the interview. Although we are aware of this problem, we see no way of circumventing it.

The wage difference between Mexico and the US measures the success of migrants based on their economic situation in the first five years after migration. While we believe that it is a suitable measure, a few caveats about measurement are in order. First, wage differences may not be the only indicator for the success of migrants. Local amenities, available housing, and other location-specific factors may contribute to the utility of a destination. If migrants maximise utility rather than income in their location choice, then we should not be surprised if a considerable share have wage differentials close to zero. While non-monetary factors may play a role in location choice, recent literature has shown that a model of income maximization can explain most of the variation in location choices of both internal and international migrants (Kennan & Walker, 2011; Grogger & Hanson, 2011).

4.2.3 Measuring Network Quality

Next we turn to the measurement of networks and information flows. The theoretical model outlines a mechanism that links the social structure of the network to the quality of information about job prospects, which in turn influences the success of migrants and the timing of migration decisions. To test this mechanism empirically, we would ideally need a measure for both the social structure of the network, and the frequency and type of information flows between the network and the migrant. From the census we cannot observe these information flows. Other datasets, for example the Mexican Migration Project (MMP) have some information on information flows, but their sample size is too small to create reliable measures for networks and have sufficient variation in network characteristics across the US. Yet, building on the theory, we can proxy the quality of information by the degree of integration of the network. As outlined in Section 2, there are good reasons to believe that better integrated networks have a better knowledge about the labour markets in a given area, because they have more interaction with the world outside the network, so that false beliefs would not easily spread in such a community. As it is most likely that migrants received some information from the network they eventually moved to, we measure for each migrant the network variable using characteristics of Mexicans that already lived in the same area.

So the question is how to measure whether a migrant community is well-integrated in the area. The literature on social networks suggests statistics that measure the degree of inbreeding homophily — the likelihood that a person only interacts with people of the same group (McPherson *et al.*, 2001). An enclave would have a high degree of homophily, as its members interact mostly with each other, but not with people outside the enclave. A direct measure of homophily requires very detailed data on the connections within a community. For every member of the community we would have to know her relation to every other member. We would not be aware of the existence of such data on a large scale. And even if there was such a dataset, mapping the exact network and calculating network statistics for communities with a few thousand observations is computationally demanding.

Following this argument, we proxy the network quality with an assimilation index, which measures the similarity between Mexicans and Americans in a given area. If Mexicans and Americans are similar with respect to age, education, fertility, occupation, and home ownership, they most likely have more interaction with Americans, and hence the network is well-integrated and has access to more accurate knowledge about the labour market. If Mexicans and Americans in an area are very different in their behavior, there is probably little interaction between the two groups.

We calculate the assimilation index at the level of *consistent PUMAs*. PUMAs (Public Use Microdata Area) are small geographic units in the US census, with a population between 100,000 and 200,000 people. They do not cross state borders, and their boundaries are re-drawn with every census, so that the size of each PUMA never exceeds 200,000 people. To make PUMAs comparable over time, the US Census Bureau has introduced *consistent* PUMAs, which have the same boundaries from 1980 to 2010, and which are larger than the original PUMAs. As we want to calculate the assimilation index of the communities before the most recent migrants arrived, we use consistent PUMAs. To every migrant who moved to a certain consistent PUMA no longer than 5 years before a census round, we match the assimilation index of Mexicans that lived in the same area in the previous census round.

Following Vigdor (2008), we calculate the assimilation index in three steps. First, we use all Mexicans and Americans in the sample, and run for each metropolitan area separate a probit regression of a binary variable (1 if Mexican, 0 if US citizen) on a number of observable characteristics,

$$P(\text{Mexican } |\boldsymbol{X}) = F(\boldsymbol{X\beta}). \tag{7}$$

$\boldsymbol{X}$ contains the following variables: marital status, gender, education (4 categories, see Appendix C.1), employment status, number of children, age, and home ownership. We also include the median income of the person's occupation in 1990 (variable ERSCOR90) to see whether migrants work in similar occupations compared to Americans. We use metropolitan areas for the probit regressions, as consistent PUMAs would in some cases be too small for the maximum likelihood function to converge. In the next steps, however, we obtain a distinct index for every consistent PUMA. Using the estimated coefficients $\hat{\beta}$, predict for every Mexican i the probability that he is in fact a Mexican.

$$\hat{p_i} = \Phi(\boldsymbol{X}\hat{\boldsymbol{\beta}}), \tag{8}$$

where Φ is the cumulative distribution function of the joint normal distribution. Let the average probability for each PUMA be $\hat{p_m}$.
Finally, we calculate the assimilation index for each PUMA as

$$\text{index}_m = 100(1 - p_m). \tag{9}$$

The sample for the calculation of the assimilation index is more restrictive than the sample used in the regressions in the next section. It consists of all Mexicans between 25 and 64 years that live in Metropolitan area with at least 20 Mexicans.

4.2.4 Descriptive Statistics

Table 3 displays the descriptive statistics for the US census in 2000 and the ACS in 2010. The average new migrant is in his late 20s, and has a lower secondary education.

Between 2000 and 2010 the losses from emigration decreased; new immigrants were on average more successful in 2010. At the same time, the increase in the standard deviation indicates a larger degree of variation in the success of new migrants. The change in the mean can be caused by at least two factors. One possibility is that real wages have increased more in the US than in Mexico. Another factor is that migrants coming after

Table 3 – Descriptive Statistics

A: US Census 2000					
Variable	Obs.	Mean	SD	Min	Max
Diaspora Characteristics					
Nr of Mexicans	53,322	186,732	257,286	26	1,110,040
Share of Mexicans	53,322	7.7	6.6	0	29.8
Assimilation 1990	43,254	73.9	14.7	35.35	99.98
Income					
Monthly income	51,870	1,477	1,096	7	14,614
Losses from emigration	51,668	-704	1,127	-13,594	1,425
Personal Characteristics					
Age	53,322	28.6	8.76	18	64
Age at immigration	53,322	26.7	8.73	18	64
High-school dropout	53,322	0.14	0.35		
Lower secondary educ	53,322	0.50	0.50		
Upper secondary educ	53,322	0.32	0.47		
Third-level education	53,322	0.04	0.20		
Married	53,322	0.48	0.50		
Nr of children	53,322	0.39	0.92	0	9

B: ACS 2010 (5-year sample)					
Diaspora Characteristics					
Nr of Mexicans	23,488	224,467	275,889	22	1,177,560
Share of Mexicans	23,488	9.87	7.82	0.01	31.4
Assimilation 2000	21,840	68.11	16.2	37.6	99.8
Income					
Monthly income	29,620	1,972	1,484	42	14,860
Losses from emigration	23,288	-1,346	1,471	-14,166	1,704
Personal Characteristics					
Age	23,488	31.85	9.17	18	64
Age at immigration	23,488	28.2	9.24	18	64
High-school dropout	23,488	0.11	0.32		
Lower secondary educ	23,488	0.42	0.49		
Upper secondary educ	23,488	0.38	0.49		
Third-level educ	23,488	0.08	0.28		
Married	23,488	0.49	0.50		
Nr of children	23,488	0.50	1.01	0	9

Note: A unit of observation is a Mexican migrant who moved to the US no longer than 5 years before the survey. Monthly income is adjusted for working hours, and conditional on working.

the census in 2000 were more skilled; the share of high-skilled immigrants — those with more than 9 years of education — increased by 10 percentage points, while the share of high-school dropouts decreased by 3 percentage points. Besides having better education, it is also possible that immigrants in 2010 had better unobservable skills.

Over time, Mexicans moved to larger communities with a higher concentration of Mexicans, and a lower degree of assimilation. The assimilation index has fewer observations than the other variables, as we were only able to calculate the assimilation index for metropolitan areas with more than 20 Mexicans.

4.3 Identification

To estimate the causal effect of network quality on the success and timing of migrants, one would ideally want to randomly assign new immigrants to different types of networks and observe the differences in the outcome of interest after they have migrated. Given that such an experiment is not available for Mexicans in the US, an alternative approach would be to find exogenous variation in the quality of networks that is unrelated to other factors that may affect the outcome of interest. In the absence of a clean quasi-experiment — for example a change in migration policies —, we rely on an instrumental variable that affects the assimilation of a local Mexican community, while it has no direct effect on the outcomes of interest.

The endogenous regressor is the assimilation index, calculated from the census in period $t-10$ years. We instrument the assimilation index in period $t-10$ years with the change in the concentration of Mexican immigrants in an area between $t-20$ years and $t-10$ years. As Figure 6 shows, there is a significant negative correlation between the change in immigrant concentration and the assimilation index. The slope coefficient of the fitted regression line is highly significant, and the change in concentration explains 65% of the variation in the assimilation index. This is intuitive, given that larger communities attract less-skilled migrants, which are typically more different from natives than previous migrants.

To be valid as an instrument, the change in immigrant concentration in the past should not have any direct effect on the success and timing of migration today, besides the indirect effect through the quality of the network. While this assumption cannot be tested, it is plausible to assume that changes in the concentration of Mexicans in an area more than 10 year ago have no direct impact on labour market outcomes today. If past settlement had a strong direct effect on the success of migrants, we would expect a

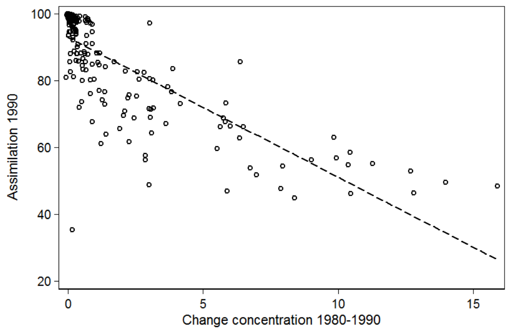

FIGURE 6 – FIRST STAGE: CORRELATION INSTRUMENT WITH ASSIMILATION.

Note: The regression line is assim = 93(0.79) − 4.79(0.15) change in concentration; $R^2 = 0.65$.

strong persistence in the success of new immigrants within an area over time. However, we cannot find this persistence in the data. The correlation over time is positive, but small: the correlation between wage differentials in 1990 and 2000 is 0.06, between 2000 and 2010 it is 0.33, and between 1990 and 2010 it is zero. The low degree of persistence suggests that current labour market success is mostly driven by current conditions in the labour market, rather than past settlement patterns.

In summary, identification hinges on the difference in the persistence of network characteristics and the success of migrants. While network characteristics persist over a long time, there is little persistence in the success of migrants. We exploit this difference in persistence by instrumenting for the network characteristics with past changes in Mexican settlement patterns, which arguably have no direct impact on contemporaneous wage differentials.

4.4 Results

4.4.1 Networks and the success of recent immigrants

In this section we estimate the impact of the network quality on the success of migrants. The basic model for all regressions is

$$y_{ict} = \alpha + \beta \ \text{assim}_{ct-10} + \ \text{avwage}_{ct} + \boldsymbol{X'\gamma}_i + \varepsilon_{ict}, \qquad (10)$$

where y_{ict} are the losses from emigration for individual i in area c at time t, which are regressed on the assimilation index at time $t - 10$. $\boldsymbol{X}$ is a vector of individual characteristics, and includes age, age squared, dummies for four education groups, and marital status. To account for differences in living standards and price levels across

Table 4 – Networks and the Success of Recent Migrants

Dependent variable: losses from emigration per month (wage in Mexico - wage in the US)

	Full sample		Positive income only		Selection model	
	OLS	IV	OLS	IV	Heckman	Heckman-IV
	(1)	(2)	(3)	(4)	(5)	(6)
A: 2000						
Assim	-4.379***	-5.608***	-4.795***	-5.607***	-4.220***	-4.294***
index 1990	(0.738)	(0.758)	(0.790)	(0.914)	(0.464)	(1.010)
R^2	0.01	0.01	0.01	0.01		0.01
Obs.	41,776	41,776	31,274	31,274	41,776	31,274
First stage						
Change share		-3.210***		-3.224***		-3.258***
1980-1990		(0.024)		(0.025)		(0.026)
F-Stat		270		268		265
B: 2010						
Assim	-3.801**	-3.053**	-2.004	-1.460	-0.908	-3.032
index 2000	(1.219)	(1.486)	(1.269)	(1.684)	(1.537)	(2.802)
R^2	0.03	0.03	0.03	0.04		0.03
Obs.	21,658	21,658	20,192	20,192	21,658	20,192
First stage						
Change share		-3.999***		-3.997***		-4.160***
1990-2000		(0.052)		(0.055)		(0.072)
F-Stat		43		42		53

Note: Dependent variable is the difference between a monthly counterfactual wage in Mexico and the actual wage in the US. The coefficients display the effect of a one-point increase in the assimilation of the network on the losses from emigration in dollar per month. In all regressions we control for age, age squared, gender, education, and marital status. In the selection model we use children as an exclusion restriction in the selection equation. In the IV regressions we instrument the assimilation index in t_{-10} with the change in the share of Mexicans from t_{-20} to t_{-10}. Standard errors, clustered at the conspuma-level, are displayed in parentheses. Standard errors in Column (6) are bootstrapped with 100 repetitions. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

districts, we control for the average wage of Americans in the same area (avwage_{ct}). ε_{ict} is an error term that captures all variation that is not explained by the other regressors. The assimilation index only varies at the area level, which is why we cluster the standard errors at the area level.

Table 4 displays the results for 2000 and 2010. Let us first consider the results for 2000. The estimates in Columns (1) and (2) are based on the entire sample, which means that they also include Mexican men with zero income. The instrument is strong, with an F-Statistic of 270, and has the expected negative sign. After controlling for average US wages and personal characteristics in the first stage, a one percentage-point increase in the concentration of Mexicans decreases the assimilation index by 3-4 points. In 2000, both coefficients lie between -4 and -5, which means that an increase in the assimilation index by one point decreases the losses from emigration by 4-5 USD per month. In terms of standard deviations, this translates into a decrease in the losses from emigration of 6% of a standard deviation for every standard deviation increase in the assimilation index. While this may not seem like a large effect, consider the difference between a network at the 25th percentile and the 75th percentile of the assimilation index. The difference in losses from earnings is 265 dollars in absolute value, which is substantial.

By using the full sample, we potentially introduce measurement error in the regressions, as we cannot guarantee that every workers with an observed income of zero indeed has no income. In columns (3) and (4) we re-estimate the basic model based on a sample of immigrants with a positive wage income. The OLS coefficient is larger in absolute value than in column (1), which can be seen as evidence of measurement error. The IV estimates, in contrast, are identical.

A problem with using the full sample is that we potentially introduce a selection bias into the model, as workers with a positive income differ in unobservable skills from workers with zero income. To account for selection-bias, we use a Heckman 2-step procedure. We first estimate a probit regression of a dummy for having positive income on all regressors in Equation (11) and a dummy for having a child in the household, which is excluded from the second stage equation. Column (5) shows the estimates from the second stage, controlling for selection by including the inverse Mills ratio. In Column (6) we address both the selection and the endogeneity problem at the same time, by using a Heckman-IV strategy as described in Wooldridge (2002, ch.17). In both models the estimated effects lie around -4.

While the results are stable across methods and samples in 2000, things are less clear in 2010. The IV is weaker than in 2000, but still strong enough, yet the estimated coefficients are only statistically significant when we use the full sample. When we exclude immigrants with zero incomes, the results preserve their negative sign, but the coefficients vary in magnitude and are statistically insignificant. One explanation for not finding a robust effect is that the financial crisis, which may have diluted the effect of networks on the success of migrants.

4.4.2 Networks and the timing of migration

Next we test the theoretical prediction that migrants with access to a better network migrate earlier. We estimate the model

$$\text{age at immigration}_{ict} = \alpha + \beta \text{ assim}_{ct-10} + \boldsymbol{X'\gamma}_i + \varepsilon_{ict}, \tag{11}$$

in which $\boldsymbol{X}$ includes dummies for four education groups and marital status. As before, standard errors are clustered at the area level, and we instrument the assimilation index with previous changes in the concentration of Mexicans. Table 5 shows the results.

Table 5 – Networks and the Timing of Migration

Dependent variable: Age at Immigration

	2000		2010	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Assim	-0.0005	-0.009	-0.0017	0.0025
index	(0.0055)	(0.008)	(0.0014)	(0.0017)
F-Stat		266		44
Obs.	43,154	43,154	21,840	21,840

Note: The coefficients display the effect of a one-point increase in the assimilation of the network on the age at immigration. In all regressions we control for education and marital status. In the IV regressions we instrument the assimilation index with the change in the geographic concentration of Mexicans. Standard errors, clustered at the conspuma-level, are displayed in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

In both census years, the results are virtually zero. Not even a large increase in the assimilation index would predict the slightest change in the timing of migration. This reduced-form result is evidence against our theoretical predictions. Despite the clear intuition of the theoretical model, as to why migrants with access to better information emigrate earlier, the data reject this mechanism.

We can think of at least three explanations for not finding an effect. First, migrants base the timing of their decision on factors other than networks. According to this interpretation, networks may well influence if people migrate at all, but conditional on migrating, they have no further influence on its timing. Factors like family situation or financial constraints may be more important for the timing than the accuracy of information about job prospects.

A second potential explanation is that our theory does not consider the intensity of communication between potential migrants and different types of networks. A well-integrated network may simply be less likely to communicate with potential migrants than an enclave. In such a setting, the advantage of receiving more accurate signals and the disadvantage of receiving fewer of them may balance each other out, which results in a zero-effect.

Third, due to data limitations, we test a dynamic model with cross-sectional data. If we had a longitudinal dataset which records the information flows between the network and the potential migrant over time, we would be able to measure the number of signals directly. Given such data is not available, we can only observe the quality of the network and timing of migration, but have no direct information on communication prior to migration.

5 Conclusion

Around the world, migrant communities differ not only in their size but also in their degree of integration in the host society. In this paper, we study how the integration of existing migrant communities affects the migration decisions and economic outcomes of future migrants. Following the economics and sociology literature on social networks, we argue that more integrated networks have a better knowledge of the labor market in the destination, and therefore give more accurate information about job opportunities to future migrants. We first explore this mechanism in a decision model with imperfect signalling, which predicts that migrants who receive information from better-integrated networks make fewer errors in their migration decisions, and they migrate earlier.

Using data on recent Mexican immigrants in the US, we test these predictions empirically. The focus on Mexico allows us to exploit a significant variation in the size and social structure of migrant communities across the United States. We measure the two variables of interest — the likelihood of making an error, and the quality of the migrant network — using the wage difference between the US and Mexico, and an assimilation index which measures the similarity of Mexicans and Americans in an area with respect to a large number of observable characteristics. To overcome omitted variable bias, we instrument the assimilation index with past changes in the diffusion of Mexicans across the US. Our results confirm the first hypothesis. Migrants with access to a better-integrated network had a significantly larger wage differential between the US and Mexico, and hence were less likely to make an error in their migration decision. We find no evidence, however, for the second hypothesis. The quality of networks has no effect on the timing of migration decisions.

With its focus on the quality of networks, this paper offers a new perspective on the role of networks in international migration. While the previous literature has proxied the strength of migrant networks through their size, we show, both theoretically and empirically, that the quality of networks has a sizable impact on the economic outcomes of migrant.

In addition, the theoretical model and the empirical findings offer new insights for the study of social networks in general. Most of the empirical literature focuses on the impact of the architecture of social networks on individual members of the network. Our paper shows that the social structure of networks also affects people outside the network — in our case potential migrants who still live in the country of origin — through the network's ability to aggregate information. If more integrated communities have better knowledge and are able to provide more accurate information, this benefits the recipients of the information.

The empirical analysis, while informative, is constrained by the available data on networks and information flows. The assimilation of migrants in a given area is a first step towards mapping the social structure of immigrant communities, but more detailed data on connections between immigrants would permit a more accurate description of the integration of these communities. Also, in our data we do not directly observe information flows, which is why we assume that migrants received information from an existing community in the destination. More detailed data on the type, frequency, and content of information flows would give important insights into the exact channels through which information flows affect migrant outcomes.

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A Appendix: Dynamic Decision Model

A.1 Derivation of p^*

To find a unique value for the threshold number of positive signals k^* in Equation (3), we determine the corresponding belief probability p^* using dynamic programming. It is possible to find p^* by looking at the optimal behavior around k^*. If $k > k^*$ the worker emigrates with certainty, which gives him the expected utility in Equation (1). $k < k^* - 1$ defines the continuation region, in which he will wait for further signals to arrive. In that case, even the next positive signal will not contain sufficient evidence for a positive migration prospect. The value of migration depends on the belief to obtain a higher income abroad, described by the value function $V_1(k)$. The value function for the continuation region has to satisfy the Bellman equation

$$rV_1(k) = \frac{1}{dt}\mathbb{E}\left[dV_1(k)\right], \tag{12}$$

which is derived as follows. The value of lifetime income after migration is $V_1(k)$. In the continuation region $V_1(k)$ has to equal the expected lifetime income after an instant dt, discounted to time t, $V_1(k) = \frac{1}{1+rdt}\mathbb{E}\left[V_1(k+1)\right]$. Multiplying by $\frac{(1+rdt)}{dt}$ and noting that $\mathbb{E}\left[V_1(k+1)\right] - V_1(k) = \mathbb{E}\left[dV_1(k)\right]$, we get Equation (12).
To determine the value function $V_1(k)$, we use the Bellman equation and construct

$$\begin{aligned} V_1(k) = \frac{1}{1+r} & \left[p(k)\left(\lambda V_1(k+1) + (1-\lambda)V_1(k-1)\right)\right. \\ & \left. + \left(1-p(k)\right)\left(\lambda V_1(k-1) + (1-\lambda)V_1(k+1)\right)\right]. \end{aligned} \tag{13}$$

Equation (13) states that the value of the option to migrate now must equal the discounted value of the option after the next signal has arrived. It is helpful to look at the game tree in Figure 2 when interpreting Equation (13). Consider the first half of the RHS of Equation (13). With probability $p(k)$ he gets a good job, so that he is at the upper node of information set 1. But because the signal from the network is not entirely truthful, he ends up at the upper node of 2A with probability λ and at the upper node of 2B with probability $1-\lambda$. At 2A the value function is $V(k+1)$, at 2B it is $V(k-1)$. The interpretation of the second half of Equation (13) is analogous.
With some algebraic manipulation, we can write Equation (13) as a second-order difference equation. We first re-write Equation (13) as

$$\begin{aligned}(1+r)V_1(k) &= V_1(k+1)\left(2p(k)\lambda + 1 - \lambda - p(k)\right) \\ &\quad + V_1(k-1)\left(p(k) - 2p(k)\lambda + \lambda\right)\end{aligned} \tag{14}$$

Using Equation (2) and defining $\zeta := \frac{1-p_0}{p_0}$, the two expressions in parentheses on the RHS reduce to

$$2p(k)\lambda + 1 - \lambda - p(k) = \frac{\lambda^{k+1} + \zeta(1-\lambda)^{k+1}}{\lambda^k + \zeta(1-\lambda)^k},$$

and

$$p(k) - 2p(k)\lambda + \lambda = \frac{\lambda(1-\lambda)\left(\lambda^{k-1} + \zeta(1-\lambda)^{k-1}\right)}{\lambda^k + \zeta(1-\lambda)^k}.$$

Inserting these into equation (14) and defining $F(k) \equiv \left(\lambda^k + \zeta(1-\lambda)^k\right) V_1(k)$ yields

$$F(k+1) - (1+r)F(k) + \lambda(1-\lambda)F(k-1) = 0. \tag{15}$$

As shown by Thijssen *et al.* (2004), Equation (15) has the general solution $F(k) = A\beta^k$. A is a constant and β is a solution to the fundamental quadratic,[12] which is an upward pointing parabola with a global minimum at $\beta = \frac{r+\mu}{2\mu}$,

$$Q(\beta) = \beta^2 - (1+r)\beta + \lambda(1-\lambda).$$

The fundamental quadratic has two real roots

$$\beta_{1,2} = \frac{1+r}{2} \pm \frac{1}{2}\sqrt{(1+r)^2 - 4\lambda(1-\lambda)}.$$

The expression under the square root is positive due to $\frac{1}{2} < \lambda < 1$.
The general solution to Equation (15) is

$$F(k) = A_1\beta_1^k + A_2\beta_2^k,$$

where A_1 and A_2 are constants. A_1 will have to be determined from the dynamic optimization problem. For the value function to be well-behaved, we require $A_2 = 0$. If the number of bad signals goes to infinity, i.e. $k \to -\infty$, the value of the option to migrate

[12] A second-order homogeneous linear difference Equation is of the form $y(x+2)+ay(x+1)+by(x) = 0$. The corresponding fundamental quadratic is $\beta^2 + a\beta + b = 0$.

should go to zero, which can only be ensured if $A_2 = 0$. Hence, the value function for $k < k^*$ is

$$V_1(k) = \frac{A_1 \beta_1^k}{\lambda^k + \zeta(1-\lambda)^k}.$$

The optimization problem has three unknown variables, A_1, p^* and k^*. To obtain the threshold belief probability p^* and the constant A_1, we have to consider the two threshold numbers of signals $k = k^*$ and $k = k^* - 1$. At $k = k^*$ the worker is indifferent between migrating and waiting. Hence, the *value-matching condition* $V_1(k^*) = \mathbb{E}(U(k^*))$ has to be satisfied. At $k = k^* - 1$, the next good signal will either make him indifferent between migrating and staying, while in the case of a bad signal he will strictly prefer staying. Consequently, starting from a number of signals $k = k^* - 1$ he will never strictly prefer emigrating after the next signal has arrived, so that $k^* - 1$ is part of the continuation region. The *continuity condition* $V_1(k^* - 1) = \mathbb{E}(U(k^* - 1))$ states that the value of the option to postpone the migration decision has to equal the expected utility from migration now. These two conditions, together with Equation (3) determine a unique solution for the three unknowns. The value-matching condition yields

$$A_1 = \frac{1}{\beta_1^k} \left(\lambda^k (w^G - M) + \zeta(1-\lambda)^k (w^B - M) \right).$$

The continuity condition is

$$A_1 = \frac{1}{\beta_1^{k-1}} \left(\lambda^{k-1} (w^G - M) + \zeta(1-\lambda)^{k-1} (w^B - M) \right).$$

Equating the continuity condition and the value matching condition and dividing by $\lambda^k + \zeta(1-\lambda)^k$, we have

$$p^*(w^G - M) + (1-p^*)(w^B - M) = p^* \beta_1 \frac{(w^G - M)}{\lambda} + (1-p^*)\beta_1 \frac{(w^B - M)}{1-\lambda}$$
$$\Leftrightarrow p^* \left(w^G - w^B - \frac{\beta_1 (w^G - M)}{\lambda} + \frac{\beta_1 (w^B - M)}{1-\lambda} \right) = (w^B - M) \frac{\beta_1 - (1-\lambda)}{1-\lambda}.$$

Dividing by $(w^B - M)$ and solving for p^* gives the threshold belief probability

$$p^* = \frac{\beta_1 - (1-\lambda)}{1-\lambda} \left[\frac{w^G - w^B}{w^B - M} - \frac{\beta_1 (w^G - M)}{\lambda (w^B - M)} + \frac{\beta_1}{1-\lambda} \right]^{-1}. \tag{16}$$

In the following, we prove that p^* is a well-defined probability.

A.2 Proof: p^* Well-defined.

Proposition. 3 *p^* is a well-defined probability.*

Proof. For p^* to be well-defined, it has to be $0 < p^* \leq 1$. For $p^*{>}0$ to hold, $\frac{\beta_1-(1-\lambda)}{1-\lambda}$ and $\left[\frac{w^G-w^B}{w^B-M} - \frac{\beta_1(w^G-M)}{\lambda(w^B-M)} + \frac{\beta_1}{1-\lambda}\right]$ have to have the same sign. Moreover, $\lambda < 1$.

$\frac{\beta_1-(1-\lambda)}{1-\lambda} > 0$ follows from $\beta_1 > 1-\lambda$.
Note that since β_1 and β_2 are the roots of an upward-pointing parabola with minimum $\frac{1+r}{2}$, it has to hold that $Q(\beta_1) = Q(\beta_2) = 0$ and $Q(\varepsilon) < 0$ for $\beta_2 < \varepsilon < \beta_1$. $Q(1-\lambda) = -r(1-\lambda) < 0$ implies $\beta_1 > 1-\lambda$.

$\left[\frac{w^G-w^B}{w^B-M} - \frac{\beta_1(w^G-M)}{\lambda(w^B-M)} + \frac{\beta_1}{1-\lambda}\right] > 0$ holds as well. Algebraic manipulation yields $\left(1-\frac{\beta_1}{\lambda}\right) > \left(1-\frac{\beta_1}{1-\lambda}\right)$, which holds by the assumption $\lambda > \frac{1}{2}$. Moreover, $\lambda < 1$ by assumption. Consequently, $p^* > 0$.
Next we show that $p^* \leq 1$. This condition is equivalent to

$$
\begin{aligned}
-1 &\leq \frac{w^G-w^B}{w^B-M} - \frac{\beta_1}{\lambda}\frac{w^G-M}{w_B-M} \\
\Leftrightarrow \left(1-\frac{\beta_1}{\lambda}\right)M &\leq \left(1-\frac{\beta_1}{\lambda}\right)w^G,
\end{aligned}
$$

which holds by assumption $w^G > M$. Hence, p^* is a well-defined probability.

B Other datasets

Given the available data on Mexican migration in the US, a researcher faces the trade-off between using a large representative dataset with little direct information on networks and without a longitudinal dimension, and small datasets that can offer this additional dimension, but that cannot provide the variation in network characteristics we would need. Using the census, we opted for sample size, which we see as a necessary condition to say anything about diaspora networks.

Other datasets on Mexicans in the US, unfortunately, are too small for our analysis. The household surveys ENET (Encuesta Nacional de Empleo Trimestral), ENADID (Encuesta Nacional de la dinámica demográfica), and the Mexican Family Life Survey (MxFLS) are conducted in Mexico, and have little information on Mexicans that already reside in the US. The Mexican Migration Project (MMP), a survey of Mexican migrants that contains both migrants and non-migrants, has some information on family and friends in the US, and on the help of these networks in crossing the border and finding a job. Numerous studies use the MMP to analyze the effect of networks on migration decisions (Munshi, 2003; Bauer *et al.*, 2005; Amuedo-Dorantes & Mundra, 2007; McKenzie & Rapoport, 2007; Bauer *et al.*, 2007). The MMP is representative of migration flows to the US (Massey & Zenteno, 2000), but it is not representative of the stocks. Additionally, it does not have any information on the characteristics of friends and family networks in the US, which is what our analysis requires.

C Data appendix

C.1 Education Groups

For the prediction of the counterfactual wages in Section 4.2.2 and for the regressions in Section 4.4 we use four broad education groups. Clustering the workers into broad education groups makes the interpretation of the estimates easier and allows us to match the Mexican and the US data. Table 6 shows the education groups for the Mexican and the US census. For the Mexican census we take the variable *years of schooling* (YRSCHL). The US census distinguishes between 11 education groups (variable EDUC).

Table 6 – Education groups in the Mexican and US census

Nr	**Education group**	**Mexican census**	**US census**
1	High-school dropouts	less than 5 years of schooling	education group 1
2	Lower secondary education	5-9 years of schooling	education groups 2-4
3	Upper secondary education	10-12 years of schooling	education groups 5-7
4	Third-level education	13 or more years of schooling	education groups 8-11

C.2 Data Cleaning US census

In the US census we exclude the following observations:

- younger than 18 and older than 64 years,
- younger than 18 at the time of immigration,
- if still enrolled in education (SCHOOL=2),
- self-employed people,
- with an annual wage income (INCWAGE) higher than 200,000 USD, as these were clear outliers,
- living in Hawaii and Alaska,
- if born to American parents in Mexico (CITIZEN=1),
- with unknown income,

- who work less than 7 hours a week (UHRSWORK) or less than 8 weeks a year (WKSWORK1, not available for 1980), or if any of these is missing,
- if they live in group quarters (hospitals, prisons, etc; GQ=3 or GQ=4)
- if they moved to a district (CONSPUMA) with at least 20 Mexicans.

To make wages comparable between the US and Mexico, we use monthly wages.

Explain here why monthly and not hourly or weekly

To obtain monthly wages, we divide the annual wages by 12. Since not all Mexicans work throughout the entire year and work full time, we adjust the income by weeks worked per year (WKSWORK1) and by hours worked in a typical workweek (UHRSWORK). In the 1980 census we obtain the adjusted monthly income by multiplying the nominal monthly income by 40 (the full time equivalent), and divide it by the actual hours worked. From 1990 onward we also have information on the average weeks per year, so that the adjusted income is calculated as

$$\text{adjusted income} = \text{ nominal income } \frac{52 * 40}{\text{weeks worked } * \text{ hours worked}}. \tag{17}$$

In the ACS the number of weeks worked comes in 6 categories, and we use the midpoints for each category (7; 20; 33; 43.5; 48.5; 51). In some rare cases the denominator in Equation (17) is very small — if the person has worked few hours and few weeks —, and we drop every observation that yields an adjusted wage income of more than 15,000 USD per month.

C.3 Mexican census

We use the 10% files of the Mexican census in 1990, 2000, and 2010 for the estimation of counterfactual wages. The following observation are excluded:

- younger than 18 and older than 64 years
- more than 100 or less than 10 hours of work per week (HRSWORK1)
- self-employed

Monthly income is taken from the variable INCEARN. As with the US census, we adjust monthly income by hours of work by multiplying it with 40 and dividing it by the usual hours of work per week (HRSWORK1). To convert the monthly wage into PPP dollars, we divide the adjusted wage by a PPP factor (price level Mexico over Price level US) and the exchange rate (pesos per dollar).[13]

[13] The PPP factor is the amount of goods in return for one dollar in the US over the amount of goods in return for one dollar in Mexico. The PPP factor was 0.48 in 1990, 0.63 in 2000, and 0.68 in 2010. The exchange rates were 2.83 pesos per dollar in 1990, 9.2845 in 2000, and 12.6287. Sources: Penn World Tables (PPP) Mexican Central Bank (Exchange Rate).

Table 7 – Counterfactual Wages: Correlations

	2000				2010			
	Baseline	PSM	Internal	Heck	Baseline	PSM	Internal	Heck
Baseline	1				1			
PSM	0.98	1			0.99	1		
Internal	0.90	0.92	1		0.92	0.93	1	
Heckman	0.95	0.94	0.80	1	0.98	0.98	0.89	1

Note: The table displays the correlations between different predictions of counterfactual wages of Mexicans in the US.

D Robustness checks

D.1 Counterfactual Wages

We predict counterfactual wages using three approaches: a sample based on propensity score matching, a sample consisting of internal migrants, and a Heckman selection model that accounts for selection into employment. Table 7 shows the correlation coefficients for the counterfactual wages on the entire sample of Mexicans in the US. The correlation coefficients are remarkably large, which gives us confidence that the straightforward prediction of Mexican wages does not suffer from severe selection bias.

D.2 PPP conversion of US wages

In the baseline scenario we construct our dependent variable as the difference between Mexican and US wages, thereby adjusting Mexican wages for purchasing power. Hence, the wage difference is the difference between the consumption values of wages in Mexico and the US. US wages of Mexican immigrants, however, may not reflect the true purchasing power, if immigrants consume a fraction of their income in their home country, send money home, or save money in order to consume at home at a later stage. Dollars earned in the US can be adjusted for purchasing power in Mexico as follows. Let s be the fraction of income consumed in Mexico and $PPP < 1$ the price level in Mexico compared to the States. The adjusted wage is then

$$\tilde{w_{US}} = w_{US}(1 - s + \frac{s}{PPP}). \tag{18}$$

If the fraction of income consumed in Mexico is greater than zero, then the purchasing power of a dollar is strictly greater than one. To demonstrate the robustness of our results, we re-calculate the wage differences, using values $s = \{0.2, 0.5, 1\}$, and re-estimate model

Table 8 – Estimation Results when a Share of US Income is Consumed in Mexico

Dependent variable: losses from emigration per month

	2000		**2010**	
	(1)	(2)	(4)	(5)
Consumption Mexico	All	Selected	All	Selected
20%	-6.25***	-6.25***	-3.33**	-1.59
	(0.85)	(1.02)	(1.62)	(1.85)
50 %	-7.32***	-7.23***	3.76**	-1.79
	(0.98)	(1.18)	(1.84)	(2.08)
100%	-8.87***	-8.84***	-4.46**	-2.12
	(1.21)	(1.45)	(2.19)	(2.48)

Note: The table displays the IV estimation results for Equation 4 for different shares of consumption in Mexico. A share of 20% means that 20% of income earned in the US is consumed in Mexico. In all regressions we control for age, age squared, education, marital status and average wages of US workers. Columns (1) and (3) use the full sample, (2) and (2) use all workers with a positive income. Standard errors, clustered at the conspuma-level, are displayed in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

with the new dependent variables. Table 8 shows that the estimated coefficients are even larger in magnitude once we account for the purchasing power US wages in Mexico. In the baseline results in Table 4 we under-estimate the effect of networks on the success of migrants. As we are not able to observe the share of consumption in Mexico, the analysis is limited by the assumption that s is constant across groups.