U.S.-MEXICO IMMIGRATION: EFFECTS OF WAGES AND BORDER ENFORCEMENT

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Abstract

I estimate a discrete choice dynamic programming model to understand how relative wages and border enforcement affect immigration from Mexico to the United States. Mexican immigrants often move to the U.S. multiple times, indicating that migration decisions are not permanent and therefore should be modeled in a lifetime setting. Also, U.S. enforcement varies considerably along the border and over time. The data shows that as enforcement at the primary crossing point increased, a greater share of illegal immigrants crossed the border at alternate points. To account for this, in the model illegal immigrants choose not only a location but also a border crossing point. I estimate the model using data on individual immigration decisions from the Mexican Migration Project. Increases in Mexican wages reduce immigration from Mexico to the U.S. and increase return migration. Simulations show that a 10% increase in Mexican wages would reduce the amount of time that individuals in the sample spend in the U.S. over a lifetime by about 11.6%. Increases in border enforcement decrease not only Mexico to U.S. immigration but also return migration. Simulations show that a 50% increase in enforcement would reduce the amount of time that individuals in the sample spend in the U.S. over a lifetime by up to 23%, depending on the allocation of the new resources along the border.

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1. Introduction

Immigration flows from Mexico to the U.S. are large. In 2004, approximately 10.5 million Mexican immigrants lived in the United States. Around 56% of the Mexicans moving to the U.S. do so illegally, compared to 17% of other immigrant groups (Hanson, 2006).

These large immigration rates have implications for both countries. Since large numbers of Mexicans are living in the U.S., immigration affects labor markets in both countries. Also, migration leads to remittances, which support development in Mexico. In 2004, remittances comprised 2.2% of Mexico's GDP, contributing more foreign exchange to Mexico than tourism or foreign direct investment (Hanson, 2006).[1] In the U.S., concern about illegal immigration affects political debate and policy. Border enforcement has been increasing since the mid-1980's, and it grew by a factor of 13 between 1986 and 2002 (Massey, 2007). Illegal immigration also affected the political debate over NAFTA, as the treaty's supporters argued that it would increase Mexican wages, which would consequently reduce illegal immigration.

In this paper, I analyze how wage differentials and U.S. border enforcement affect an individual's immigration decisions. I study this in a lifetime setting, which is important because the data shows that immigration decisions are not permanent. For example, in the dataset used in this paper, migrants moved to the U.S. an average of 2.5 times. Changes in wages and enforcement affect not only initial but also return migration decisions. Increased Mexican wages raise the value of living in Mexico, reducing Mexico to U.S. migration and increasing return migration. Increased border enforcement raises the cost of illegally moving to the U.S., reducing Mexico to U.S. migration. As enforcement increases, immigrants living in the U.S. may be more reluctant to return home, knowing that it will be harder to re-enter the U.S. in the future. This increases the duration of stays in the United States. Therefore, the overall effect of increased enforcement on the stock of illegal immigrants is ambiguous, as fewer people move, but those who do move stay in the U.S. for longer.

To analyze these questions, I estimate a discrete choice dynamic programming model where individuals choose from a set of locations in Mexico and the United States in each period. The model differentiates between legal and illegal immigrants, who face different moving costs and a different wage distribution in the United States. Empirical evidence shows that illegal immigrants receive lower wages than legal immigrants and have less opportunity for occupational advancement when living in the U.S. (Kossoudji and Cobb-Clark, 2000). Border enforcement affects the moving cost only for illegal immigrants.

[1] Woodruff and Zenteno (2007) find that close to 20% of the capital invested in urban microenterprises comes from remittances. In the ten states with the highest immigration rates, they report that almost one-third of the capital invested in microenterprises comes from remittances.

Most past research on this topic uses aggregate border patrol as a measure of enforcement. Instead, I use data on enforcement at different sections of the border. There has been a large growth in enforcement over the past 20 years, but most of it has been concentrated at certain segments of the border. Initially, most migrants crossed the border near San Diego, but as enforcement there increased, they shifted to other points along the border. This suggests that the increased enforcement affected migration behavior, even for the people who still chose to immigrate. Past work, which for the most part uses aggregate enforcement levels, misses this component of the effect of increased border patrol on immigration decisions. In the model, individuals choose where to live and, if illegally moving to the U.S., where to cross the border. Variations in enforcement along the border, combined with crossing point decisions, are used to identify the effect of border enforcement on illegal immigration.

Another contribution of this paper is to model behavior so that family decisions are related, which has been shown to be important empirically. For example, a woman is more likely to move to the U.S. if her husband is already living there. In comparison to much of the past work on this topic, I model both the decisions of the household head and spouse, allowing an individual's location choice to depend on where his spouse is living. To make this computationally feasible, I model household decisions in a two-step process: first, the household head picks a location and then the spouse decides where to live. By allowing spouses' decisions to be related, I can better understand the determinants of immigration.

I estimate the model using data on individual immigration decisions from the Mexican Migration Project (MMP). The MMP data reports where an individual was living in each year and, if he moved to the U.S. illegally, where he crossed the border. To measure border enforcement, I use data from the U.S. Customs and Border Patrol on the number of man-hours spent patrolling each border patrol sector in each year.

I use the estimated model to perform several counterfactuals. I find that increases in Mexican wages decrease both immigration rates and the duration of stays in the United States. Simulations show that a 10% increase in Mexican wages would reduce the average number of years that a person in the sample lives in the U.S. over a lifetime by 11.6%.

Recently, there has been a lot of debate in the U.S. about increasing border enforcement. My model finds that increased border enforcement would reduce both the number of people that immigrate and the number of moves per migrant. In addition, it would cause an increase in the duration of stays in the United States. Simulations show that a 50% increase in enforcement, distributed uniformly along the border, reduces the average amount of time that an individual in the sample spends in the U.S. by approximately 9.3%. If total enforcement increased by 50%, not uniformly but instead concentrated at the points along the border where it would have the largest effect, the number of years spent in the U.S. per person would decrease by 23%. This suggests that the effect of increased enforcement depends on the allocation of the new resources.

The remainder of the paper is organized as follows. Section 2 reviews the literature, and Section 3 explains the model. Section 4 details the data and provides descriptive statistics, and Section 5 explains the estimation. Section 6 shows the results, and the counterfactuals are in Section 7. Section 8 concludes.

2. Related Literature

Wages are understood to be the main driving force behind immigration from Mexico to the United States. Hanson and Spilimbergo (1999) find that increases in U.S. wages relative to Mexican wages positively affect apprehensions at the border. This indicates that, as the relative wage in the U.S. increases, people are more likely to attempt to move illegally. Rendón and Cuecuecha (2010) estimate a model of job search, savings, and migration, finding that migration and return migration depend not only on wage differentials, but also on job turnover and job-to-job transitions.

To estimate the effect of border enforcement on immigration decisions, some papers use the structural break caused by the 1986 *Immigration Report and Control Act* (IRCA), one of the first policies aimed at decreasing illegal immigration. This law increased border enforcement and legalized many illegal immigrants living in the United States. Espenshade (1990, 1994) finds that there was a decline in apprehensions at the U.S. border in the year after IRCA was implemented, but no lasting effect. Using survey data from communities in Mexico, Cornelius (1989) and Donato, Durand, and Massey (1992) find that IRCA had little or no effect on illegal immigration.

After the implementation of IRCA, there was a steady increase in border enforcement over time. A number of papers use data on the number of man-hours spent patrolling the border to measure changes in enforcement over time. Hanson and Spilimbergo (1999) find that increases in enforcement lead to a greater number of apprehensions at the border. This provides one mechanism for increased enforcement to affect moving costs, as immigrants may have to make a greater number of attempts to successfully cross the border.

Gathmann (2008) uses data from the Mexican Migration Project (MMP) to study how changes in enforcement affect explicit moving costs. She finds that increased border enforcement raises the costs paid to coyotes, who help to smuggle people across the border. This provides another mechanism for increased border enforcement to affect moving costs. She also finds that migrants cross the border at new sectors after enforcement at the main crossing point increased. I use a similar identification strategy, by comparing enforcement along the border with crossing point choices. However, I explicitly model the crossing-point choice along with immigration decisions, whereas she analyzes the binary decision for a repeat migrant to switch border crossing points.

Changes in enforcement can affect not only initial but also return migration decisions. Angelucci (2005) uses the MMP data to study how border enforcement affects initial and return migration. She finds that both the inflow and outflow of Mexican migrants are sensitive to aggregate border enforcement. Her framework permits analysis of initial and return migration decisions separately using a reduced form framework. I perform counterfactual analyses to calculate the net effect of changes in enforcement on illegal immigration. Thom (2010) develops and estimates a model of circular migration for Mexican immigrants, incorporating savings decisions. He finds that border enforcement reduces migration rates and increases trip durations.

In this paper, I use the discrete choice dynamic programming framework of Kennan and Walker (2010), who develop an econometric model in which agents move within the U.S. based on differences in expected income. Individuals decide where to live in each period; therefore, people can make multiple moves. I allow the option of moving outside of the country and modify the model to account for the differences caused by illegal immigration. Hong (2010) applies a similar framework to U.S. Mexico immigration. In comparison to this paper, he focuses on the legalization process.

Previous empirical work highlights the importance of controlling for marital status and the location of a person's spouse when studying migration from Mexico to the United States. Cerrutti and Massey (2001) examine the determinants of female Mexican migration to the United States. They find that, when women move, they are almost always following another family member. On the other hand, almost half of the male migrants leave for the U.S. before or without a family member. Marital status also affects return migration decisions, as Massey and Espinosa (1997) find that illegal immigrants are more likely to return to Mexico if they are married. Most past structural work on migration does not allow for a spouse's decisions to affect one's behavior. A notable exception is Gemici (2008), who estimates a dynamic model of migration decisions with intra-household bargaining using U.S. data. In her model, married couples make a joint decision on where to live, whereas the data from Mexico shows that couples often live in different locations. I extend the literature to incorporate these observations into my model specification, allowing the spouse's decisions to affect migration behavior.

3. Model

At each point in time, a person chooses a location from a set of places in Mexico and in the United States. I assume that people know their wage draws in all locations. If moving to a new location, a person pays a moving cost. At the start of each period, he sees a set of payoff shocks to living in each location. The shocks are random, i.i.d.

across locations and time, and unobserved by the econometrician. After seeing these shocks, he decides where to live.

A person's decisions depend on whether he is able to move to the U.S. legally. Legal status affects the cost of moving from Mexico to the U.S. and the wage distribution in the United States. The moving cost for illegal immigrants depends on U.S. border enforcement. In addition, in the model, people moving illegally to the U.S. choose a location and a border crossing point. I assume that people who choose to move to the U.S. are successful. Empirical evidence shows that when migrants are caught at the border, they attempt to enter the U.S. again.[2] Therefore, it is reasonable to assume that they will eventually succeed. I also assume that once an illegal immigrant enters the U.S., there is no chance that he will be deported. Supporting this assumption, Espenshade (1994) finds that only 1-2% of illegal immigrants living in the U.S. are caught and deported in each year.

Decisions also depend on a person's marital status. For married couples, utility depends on whether a person is living at the same location as his spouse. To simplify the problem, I assume that a person's utility depends on whether he is in the same country as his spouse. This reduces the state space, as the spouse's location only has two possible elements. Following the empirical results in Cerrutti and Massey (2001) and Massey and Espinosa (1997), I also make some assumptions on the choice sets available to individuals. For each household, I define a primary and a secondary mover. I assume that the secondary mover cannot live in the U.S. unless the primary mover is living there.[3] I also make some assumptions on the timing of decisions, which is shown in Figure 1. The primary mover picks a location first. When making his decision, the primary mover knows the probability that his spouse will pick a given location, conditional on his choice, where this probability comes from the distribution of the shocks. After the primary mover makes a decision, the secondary mover learns her payoff shocks and decides where to live. Therefore when the secondary mover decides where to live, she knows her spouse's location.[4]

The state space and consequently value functions for primary and secondary movers are slightly different. When making a decision, the secondary mover knows

[2]See Passel, Bean, and Edmonston (1990), Kossoudji (1992), Donato, Durand, and Massey (1992), Blejer, Johnson, and Porzecanski (1978), and Crane, Asch, Heilbrunn, and Cullinane (1990).

[3]These assumptions are made to simplify computation; however, they are supported by the data. When individuals in a married household move to the U.S., they either move at the same time or there is one individual who always moves first. If one household member moves to the U.S., returns, and then the other household member moves to the U.S., then these assumptions would be violated. This are very few observations where this occurs.

[4]These assumptions on the timing of decisions do not allow for a greater likelihood of spouses moving to the U.S. at the same time. However, the data shows that couples usually move at different times. Of the wives that move to the U.S., only 20% move at the same time as their husband and the remainder move at a later date.

her spouse's location in the current period, whereas the primary mover knows his spouse's previous period location. Expectations over a spouse's future decisions affects a person's behavior. The secondary mover knows the probability that her spouse will make a given choice in the next period. For example, if a person lives in Mexico but her spouse in the U.S., the probability that her spouse will return to Mexico in the next period affects her decision. If there is a high chance that her spouse will return home, then she has less of an incentive to move to the United States. The primary mover is unsure where his spouse will live in the current period. The decision on whether to move to the U.S. depends on the probability that his spouse will join him.

3.1 Value Function

Denote the set of locations in the U.S. as J_U, those in Mexico as J_M, and the set of border crossing points as C. People moving to the U.S. illegally pick both a location and a border crossing point.

At the start of each period, a person learns whether or not he can move legally at that time.[5] I assume that once a person is able to immigrate legally, this option remains with him forever. However, a person who currently cannot legally immigrate only knows the probability that he will be able to move legally in the future. I use z_t to indicate whether or not a person can move to the U.S. legally, where $z_t = 1$ means a person can move to the U.S. legally and $z_t = 2$ means that he cannot.

I use m to denote a person's marital status, where $m = 1$ is the primary mover and $m = 2$ is the secondary mover. In the remainder of this section, I solve the problem for primary and secondary movers. The case for single people is trivial once these two cases are solved, as it is the same as except that there is no spouse's location in the state space.[6]

Because the problem is solved by backwards induction and the secondary mover makes the last decision, it is logical to start with the secondary mover's problem.

3.1.1 Secondary Movers

I use the superscripts 1 and 2 to denote locations and characteristics of the primary and secondary mover, respectively. I assume that secondary movers can only live in the U.S. if the primary mover is living there. The choice set can be limited, depending

[5]This assumption is made because some people may have applied to immigrate legally and therefore expect that there is some chance that they will be able to legally immigrate in the future.

[6]I do not allow for expectations over transitions between being single and married. Therefore, a person who is single expects to remain single forever. In the data, people do transition between states. I assume they solve the value function corresponding to their current marital status.

on the location of the primary mover. Denote $J^2(\ell_{t-1}^2, z_t^2, \ell_t^1)$ as the location choice set for a secondary mover with previous location ℓ_{t-1}^2, legal status z_t^2, and spouse in location ℓ_t^1, where

$$J^2(\ell_{t-1}^2, z_t^2, \ell_t^1) = \begin{cases} J_M & \text{if } \ell_t^1 \in J_M \\ J_M \cup (J_U \times C) & \text{if } \ell_{t-1}^2 \in J_M \text{ , } \ell_t^1 \in J_U \text{ and } z_t^2 = 2 \\ J_M \cup J_U & \text{otherwise} \end{cases}$$

If the primary mover is living in Mexico, then the secondary mover can only live in Mexico. If the primary mover is living in the U.S., then the secondary mover can choose from all locations. If she moves to the U.S. illegally, she has to pick a location and a border crossing point.

The value function at time t depends on a person's location in the previous period (ℓ_{t-1}^2), her characteristics X_t^2 (which include age), and her legal status (z_t^2). Since the secondary mover picks her location after the primary mover, she knows where her spouse is living when she makes a decision. Therefore the location of the spouse (ℓ_t^1) is part of the state space. The spouse's location affects utility, as I assume that married couples prefer to live at the same location. The characteristics and legal status of one's spouse (X_t^1 and z_t^1) are part of the state space. The probability that the primary mover makes a given decision in future periods, which depends on his characteristics, affect the secondary mover's decision. For example, if the primary mover is living in the U.S., there is a chance he will return to Mexico in the next period. If this is a likely event, then the secondary mover has less of an incentive to move to the U.S. today. To simplify notation, denote Δ_t^2 as the characteristics and legal status of the secondary mover and her spouse, so $\Delta_t^2 = \{X_t^2, z_t^2, X_t^1, z_t^1\}$. The value function also depends on a person's wage draw in all locations. I assume that wages are a deterministic function of characteristics, legal status, and location, so the wage in location j can be written as $w(X_t^2, z_t^2, j)$.

In each period, a person receives a payoff shock to living in each location. These are drawn independently from the Type I extreme value distribution. Denote the set of payoff shocks at time t as $\eta_t^2 = \{\eta_t^j\}$, where j indexes locations. After seeing her set of payoff shocks, she picks the location with the highest value. The value function is defined as follows:

$$V_t^2(\ell_{t-1}^2, \Delta_t^2, \ell_t^1, \eta_t^2) = \max_{j \in J^2(\ell_{t-1}^2, z_t^2, \ell_t^1)} v_t^2(j, \ell_{t-1}^2, \Delta_t^2, \ell_t^1) + \eta_{jt}^2 \tag{1}$$

The value of living in each location has a deterministic and a random component ($v_t^2(\cdot)$ and η_t^2, respectively).

The deterministic component of living in a location consists of the flow payoff (including utility and moving costs) and the discounted expected value of living there at the start of the next period. The utility flow depends on a person's wage, location j, characteristics X_t^2, legal status z_t^2, and spouse's location ℓ_t^1, and it is written as $u(j, X_t^2, z_t^2, \ell_t^1)$. The wage draw is not included as an input in the utility function because it is a deterministic function of characteristics, legal status, and location. Utility depends on whether or not a person is at her home location, which is included in her characteristics X_t^2. Empirical evidence shows that people prefer to live at their home location. In the data, immigrants who move to the U.S. and then return to Mexico are most likely to move to their home location. Utility also depends on whether or not a person is at the same location as her spouse. The moving cost is the second component of the flow payoff. It depends on which locations a person is moving between, her characteristics, and her legal status. Denote the cost of moving from location ℓ_{t-1}^2 to location j as $c_t(\ell_{t-1}^2, j, X_t^2, z_t^2)$. The flow payoff of living in location j, denoted at $\tilde{v}_t(\cdot)$, is defined as

$$\tilde{v}_t(j, \ell_{t-1}^2, X_t^2, z_t^2, \ell_t^1) = u(j, X_t^2, z_t^2, \ell_t^1) - c_t(\ell_{t-1}^2, j, X_t^2, z_t^2)$$

The flow payoff is utility minus moving costs, where, if a person is staying at the same location, the moving cost is zero. The deterministic component of living in a location is the flow payoff plus the discounted expected value of living there in the next period:

$$v_t^2(\cdot) = \tilde{v}_t(j, \ell_{t-1}^2, X_t^2, z_t^2, \ell_t^1) + \beta E\left[V_{t+1}^2(j, \Delta_{t+1}^2, \ell_{t+1}^1, \eta_{t+1}^2)\right]$$

When calculating the continuation payoffs, there are three forms of uncertainty. First, there is uncertainty over future preference shocks. Second, for a person who currently cannot immigrate legally, there is uncertainty over whether she will be able to immigrate legally in future periods. Finally, there is uncertainty over the primary mover's location in the next period.

I assume a finite horizon. The model can be solved using backwards induction, following McFadden (1973) and Rust (1987). First I integrate out the payoff shocks. For a given legal status and location of primary mover, the expected future value is given by

$$\begin{aligned} E\left[V_{t+1}^2(j, \Delta_{t+1}^2, \ell_{t+1}^1, \eta_{t+1}^2) | z_{t+1}^2, \ell_{t+1}^1\right] &= E\left[\max_{k \in J^2(j, z_{t+1}^2, \ell_{t+1}^1)} v_{t+1}^2(k, j, \Delta_{t+1}^2, \ell_{t+1}^1) + \eta_{k,t+1}^2\right] \\ &= \log\left(\sum_{k \in J^2(j, z_{t+1}^2, \ell_{t+1}^1)} \exp\left(v_{t+1}^2(k, j, \Delta_{t+1}^2, \ell_{t+1}^1)\right)\right) + \gamma \end{aligned} \tag{2}$$

In equation (2), γ is Euler's constant ($\gamma \approx 0.58$).

There are two unknown states: future legal status and primary mover's location, both of which are discrete. Denote the probability of being in the state with legal status z_{t+1}^2 and having a spouse in location ℓ_{t+1}^1 in the next period as $\rho_t^2(z_{t+1}^2, \ell_{t+1}^1 | j, \Delta_t^2, \ell_t^1)$. This is conditional on a person and her spouse's current period location, characteristics, and legal status. The transition probabilities are explained in more detail in section 3.1.3. The unconditional expected value is given by

$$
\begin{aligned}
&EV_{t+1}^2(j, \Delta_{t+1}^2, \ell_{t+1}^1, \eta_{t+1}^2) = \\
&\sum_{z_{t+1}^2, \ell_{t+1}^1} \rho_t^2(z_{t+1}^2, \ell_{t+1}^1 | j, \Delta_t^2, \ell_t^1) \times E\left[V_{t+1}^2(j, \Delta_{t+1}^2, \ell_{t+1}^1, \eta_{t+1}^2) | z_{t+1}^2, \ell_{t+1}^1\right],
\end{aligned}
$$

where the last term is the expected value for a given state, calculated in equation (2).

I calculate the probability that a person will choose location j at time t. This probability is important for two reasons. First, it is used to develop the likelihood function. In addition, it will be used to calculate the transition probabilities for the primary mover, who is concerned with the probability that his spouse makes a given decision. For instance, if the primary mover moves to the U.S., he is interested in the probability that his spouse will join him.

Since I assumed that the payoff shocks are distributed with an extreme value distribution, the choice probabilities take a logit form. To calculate the probability that a person picks location j, the numerator is given by the exponential of the $v_t^2(\cdot)$ for location j, whereas the denominator is the sum, over locations, of the exponential of $v_t^2(\cdot)$:

$$
P_t^2(j | \ell_{t-1}^2, \Delta_t^2, \ell_t^1) = \frac{\exp\left(v_t^2(j, \ell_{t-1}^2, \Delta_t^2, \ell_t^1)\right)}{\sum_{k \in J(\ell_{t-1}^2, z_t^2, \ell_t^1)} \exp\left(v_t^2(k, \ell_{t-1}^2, \Delta_t^2, \ell_t^1)\right)} \tag{3}
$$

3.1.2 Primary Movers

A primary mover chooses a location in each period. If moving to the U.S. illegally, he also picks a border crossing point. In comparison to secondary movers, the set of location choices for the primary mover does not depend on the location of his spouse. Denote the choice set for primary movers as $J^1(\ell_{t-1}^1, z_t^1)$, where

$$
J^1(\ell_{t-1}^1, z_t^1) = \begin{cases} J_M \cup (J_U \times C) & \text{if } \ell_{t-1}^1 \in J_M \text{ and } z_t^1 = 2 \\ J_M \cup J_U & \text{otherwise} \end{cases}
$$

Since he picks a location first, the primary mover does not know where his spouse will live in each period. He knows the probability that his spouse will make a given choice, which depends on where he lives. For example, if he chooses to live in the U.S., he knows the probability that his spouse will join him. Even though the primary mover does not know where his spouse will live in the current period, the spouse's previous location ℓ^2_{t-1} is known and is part of the state space.

The primary mover's flow payoff, conditional on his spouse's location, is defined as

$$\tilde{v}_t(j, \ell^1_{t-1}, X^1_t, z^1_t, \ell^2_t) = u(j, X^1_t, z^1_t, \ell^2_t) - c(\ell^1_{t-1}, j, X^1_t, z^1_t)$$

In this case, in comparison to the secondary mover's problem, he does not know his spouse's location, and therefore does not know his exact utility or flow payoff in each location. Instead, he knows his expected flow payoff:

$$E_{\ell^2_t}\left[\tilde{v}_t(j, \ell^1_{t-1}, X^1_t, z^1_t, \ell^2_t)|X^2_t, z^2_t\right] = \sum_k P^2_t(k|\ell^2_{t-1}, \Delta^2_t, j)u(j, X^1_t, z^1_t, k) - c(\ell^1_{t-1}, j, X^1_t, z^1_t) \tag{4}$$

In equation (4), $P^2_t(\cdot)$ is the probability that the secondary mover lives in a given location, conditional on the primary mover's choice. This was defined in the previous section in equation (3). The expected flow payoff from living in a location is a weighted average of his flow payoff in each of the possible outcomes.

The state space for primary movers is similar to that of secondary movers. It includes his previous location, his characteristics and legal status, and the secondary mover's characteristics and legal status. In comparison to the secondary mover's problem, his spouse's previous period location, not her current period location, is in the state space. Denote Δ^1_t as the characteristics and legal status of the primary mover and his spouse, where $\Delta^1_t = \{X^1_t, z^1_t, X^2_t, z^2_t\}$. I define the value function for the primary mover as follows:

$$V^1_t(\ell^1_{t-1}, \Delta^1_t, \ell^2_{t-1}, \eta^1_t) = \max_{j \in J(\ell^1_{t-1}, z^1_t)} v^1_t(j, \ell^1_{t-1}, \Delta^1_t, \ell^2_{t-1}) + \eta_{jt} \tag{5}$$

The function $v^1_t(\cdot)$, which is the deterministic component of the value of living in a location, includes the expected flow payoff and the discounted expected value of living there in the next period:

$$v^1_t(\cdot) = E_{\ell^2_t}\left[\tilde{v}_t(j, \ell^1_{t-1}, X^1_t, z^1_t, \ell^2_t)|X^2_t, z^2_t\right] + \beta E V^1_{t+1}(j, \Delta^1_{t+1}, \ell^2_t, \eta^1_{t+1})$$

The unknown states are future legal status and the location of the secondary mover in the current period. For a given state, the continuation value is calculated as follows:

$$E\left[V^1_{t+1}(j, \Delta^1_{t+1}, \ell^2_t, \eta^1_{t+1})|z^1_{t+1}, \ell^2_t\right] \quad = \quad E\left[\max_{k \in J(j, z^1_{t+1})} v^1_{t+1}(k, j, \Delta^1_{t+1}, \ell^2_t) + \eta^1_{j,t+1}\right]$$

$$= \log \left(\sum_{k \in J(j, z^1_{t+1})} \exp v^1_{t+1}\left(k, j, \Delta^1_{t+1}, \ell^2_t\right) \right) + \gamma$$

Let $\rho^1_t(z^1_{t+1}, \ell^2_t | j, \Delta^1_t, \ell^2_{t-1})$ be the probability that a primary mover is in a given state at time $t+1$. Then,

$$EV^1_{t+1}(j, \Delta^1_{t+1}, \ell^2_t, \eta^1_{t+1}) = \sum_{z^1_{t+1}, \ell^2_t} \rho^1_t(z^1_{t+1}, \ell^2_t | j, \Delta^1_t, \ell^2_{t-1}) \times E\left[V^1_{t+1}(j, \Delta^1_{t+1}, \ell^2_t, \eta^1_{t+1}) | z^1_{t+1}, \ell^2_t\right]$$

The transition probabilities are explained in more detail in Section 3.1.3.

To develop the transition probabilities for the secondary mover and to compute the likelihood function, I calculate the probability that the primary mover picks a location in each period. Using the properties of the extreme value distribution, the probability that a primary mover picks location j is given by

$$P^1_t(j | \ell^1_{t-1}, \Delta^1_t, \ell^2_{t-1}) = \frac{\exp\left(v^1_t(j, \ell^1_{t-1}, \Delta^1_t, \ell^2_{t-1})\right)}{\sum_{k \in J(\ell^1_{t-1}, z^1_t)} \exp\left(v^1_t(k, \ell^1_{t-1}, \Delta^1_t, \ell^2_{t-1})\right)} \tag{6}$$

3.1.3 Transition Probabilities

The transition probabilities are over future legal status and a spouse's future decisions. I assume these events are independent.

I assume that the agent has the same information as the spouse about the spouse's future decisions. The probability that a person's spouse lives in a given location comes from his choice probabilities, which were defined in the previous sections. Denote the probability that a person with characteristics X_t remains an illegal immigrant at time $t+1$ as $\delta(X_t)$. Then a person can immigrate legally in the next period with probability $1 - \delta(X_t)$.[7] I assume that being able to immigrate legally is an absorbing state, so once a person can immigrate legally it remains that way forever.

Define the matrices $A(X_t)$ and $Z(z_t)$ as

$$A(X_t) = \begin{bmatrix} 1 & 1 - \delta(X_t) \\ 0 & \delta(X_t) \end{bmatrix}$$

$$Z(z_t) = \begin{bmatrix} \mathbb{1}(z_t = 1) \\ \mathbb{1}(z_t = 2) \end{bmatrix}$$

In the matrix $Z(z_t)$, the expression $\mathbb{1}(\cdot)$ is an indicator function which equals 1 if the expression inside the parentheses is true and 0 otherwise. Multiplying $A(X_t)$ times

[7] Due to the nature of U.S. immigration laws, the probability that a person can become a legal immigrant depends on the legal status of his spouse. I will add this to the model and estimation in future work.

$Z(z_t)$ gives the probability that a person has a given legal status in the next period, where the top element is the probability that a person can immigrate legally and the bottom element is the probability that he cannot. Legal immigrants cannot lose the ability to move legally.

Denote the matrices Λ_t^1 and Λ_t^2 as the transition probabilities into legal and illegal status for primary and secondary movers, respectively, where

$$\Lambda_t^1(\ell_t^2|j,\Delta_t^1,\ell_{t-1}^2) = \begin{bmatrix} \rho_t^1(z_{t+1}^1 = 1, \ell_t^2|j,\Delta_t^1,\ell_{t-1}^2) \\ \rho_t^1(z_{t+1}^1 = 2, \ell_t^2|j,\Delta_t^1,\ell_{t-1}^2) \end{bmatrix}$$

$$\Lambda_t^2(\ell_{t+1}^1|j,\Delta_t^2,\ell_t^1) = \begin{bmatrix} \rho_t^2(z_{t+1}^2 = 1, \ell_{t+1}^1|j,\Delta_t^2,\ell_t^1) \\ \rho_t^2(z_{t+1}^2 = 2, \ell_{t+1}^1|j,\Delta_t^2,\ell_t^1) \end{bmatrix}$$

In each case, the top element in the matrix is the probability of being in a state where one is a legal immigrant, and the bottom element is when one is an illegal immigrant. There is uncertainty over the spouse's location, legal status, and wages in new locations. Then

$$\begin{aligned} \Lambda_t^1(\ell_t^2|j,\Delta_t^1,\ell_{t-1}^2) &= A(X_t^1)Z(z_t^1)P_t^2(\ell_t^2|\ell_{t-1}^2,\Delta_t^2,\ell_t^1) \\ \Lambda_t^2(\ell_{t+1}^1|j,\Delta_t^2,\ell_t^1) &= A(X_t^2)Z(z_t^2)P_{t+1}^1(\ell_{t+1}^1|\ell_t^1,\Delta_t^1,\ell_t^2) \end{aligned}$$

For primary movers, there is uncertainty over where the secondary mover will live in that period. This is represented by the function $P_t^2(\cdot)$, which comes from the secondary movers choice probabilities defined in equation (3). Likewise, for secondary movers, there is uncertainty over the primary movers location in the next period. This is represented by the function $P_{t+1}^1(\cdot)$, which comes from the primary mover's choice probabilities defined in equation (6). There is also uncertainty over future legal status.

4. Data and Descriptive Statistics

I estimate the model using data from the Mexican Migration Project (MMP), a joint project of Princeton University and the University of Guadalajara.[8] The MMP is a repeated cross-sectional dataset that started in 1982, with the last currently available round from 2009. They randomly select households from specific communities in Mexico to interview during each round. If a household reports that a family member currently lives in the U.S., the MMP researchers ask for information about that person. Interviewers also survey individuals from each community who are living in the United States. However, the sample is not representative of Mexico, as they pick rural

[8] The data and a discussion of the survey methodology is posted on the MMP website: mmp.opr.princeton.edu.

communities with high migration propensities. Western-central Mexico, the region with the highest migration rates historically, is over-sampled.[9]

To estimate the model, I need a panel dataset with each individual's location at each point in time. For household heads and spouses, the MMP collects a lifetime migration history. I use this information to construct a panel dataset. The survey asks each individual if and when they were allowed to move to the U.S. legally. For people who move to the U.S. illegally, the dataset records at which point they cross the border. Immigrants report the closest city in Mexico to where they crossed the border. I match this to the nearest U.S. border patrol sector.

This paper studies how changes in wages and border enforcement affect immigration decisions. Border patrol was fairly low and constant up to the 1986 *Immigration Reform and Control Act* (IRCA). Because the data has lifetime histories, the data in the sample spans many years, starting in the early 1900's. Computing the value function for each year is costly, so I limit the sample time frame to years in which there are changes in enforcement levels. For this reason, I study behavior starting in 1980. To avoid an initial condition problem, I only include individuals who were age 17 in 1980 or after. This leaves me with a sample size of 9,214, in which I observe each person's location from age 17 until the year surveyed.[10]

The MMP has wage data when people are in the U.S., which I use to compute the wage distribution for Mexican migrants living in the United States. The MMP also records wages in Mexico; however, there are limited wage observations per person. In addition, to estimate the model, I need information on wages in all Mexican states, which is not available in the MMP due to their sampling design. Therefore, for Mexican wages, I use the Encuesta Nacional de Ocupación y Empleo (ENOE), Mexico's national labor force survey.

To measure border enforcement, I use data from U.S. Customs and Border Protection (CBP) on the number of man-hours spent patrolling each sector of the border (taking a monthly average for each year).[11] CBP divides the U.S.-Mexico border into 9 regions, and the data reports the man-hours spent patrolling each sector.

4.1 Descriptive Statistics

Table 1 shows the characteristics of the sample, divided into 5 groups: people who move internally, people who move to the U.S., people who move internally and to the U.S., non-migrants, and people who can immigrate legally. The mover groups, especially those moving to the U.S., are dominated by men. A large proportion of

[9] The MMP website shows a map of included communities: http://mmp.opr.princeton.edu/research/maps-en.aspx.

[10] The enforcement data ends at 2004. Therefore I only include location decisions up to 2004.

[11] I thank Gordon Hanson for providing this data.

the sample is married. Internal movers and legal immigrants are the most educated, whereas illegal immigrants are the least educated. The literature finds that returns to education are higher in Mexico than in the U.S., possibly explaining why educated people are less likely to immigrate illegally. In addition, illegal immigrants do not have access to the full U.S. labor market, and therefore may not be able to find jobs that require higher levels of education. Looking at the sample size in each group, we see that people who can immigrate legally make up about 5% of the sample.

Between 1980 and 2004, an average of 2.6% of the people living in Mexico moved to the U.S. in each year. Return migration rates are high, as in each year about 21% of the people living in the U.S. returned to Mexico. Furthermore, many migrants move to the U.S. more than once over the course of a lifetime. On average, each migrant moved to the U.S. 2.5 times. Since repeat and return migration are common, it is important to model these decisions using a lifetime framework.

Table 2 shows the average number of moves per migrant, splitting the sample by gender, education, and age. Men move more, and the number of moves decreases with education and increases with age. The migration literature finds that younger people are more likely to move. Table 2 shows that, of the migrant population, people continue to move to the U.S. even at older ages.

4.2 Immigration Decisions

To understand the determinants of immigration decisions, I estimate how different factors affect the probability that a person moves to the U.S., the probability that a migrant returns to Mexico, and the probability that a person has the option to move to the U.S. legally.

Using a probit regression, I first estimate the probability that a person who lives in Mexico moves to the U.S. in a given year. The coefficient estimates are reported in the first column of Table 3. As education increases above 11 years, the probability of moving to the U.S. decreases. This could be because of high returns to skills in Mexico. The coefficient on age is negative, supporting the human capital model, which predicts that younger people are more likely to move because they have more time to earn higher wages. Empirical studies find that people with larger networks in the U.S. are more likely to immigrate. Using family members as a measure of networks, I find that having a family member in the U.S. makes a person more likely to immigrate. To account for this, in the structural estimation, I will allow for family networks to affect both wages in the U.S. and moving costs. In the model, I allow for the decisions of spouses to be related, implying that a person should be more likely to immigrate if their spouse is living in the United States. Supporting this assumption, this regression shows that people who have spouses living in the U.S. are more likely to immigrate. In addition, people who are married are less likely to move. The regression also shows that people who have been to the U.S. before are more likely to move.

Next, I estimate the probability that a person currently living in the U.S. returns to Mexico in a given year. These results are shown in the second column in Table 3. There is no clear trend with regard to education. Up to age 30, as people get older, they are less likely to return migrate. After age 30, the probability of returning to Mexico increases with age. Legal immigrants and people with family networks in the U.S. are less likely to return home. People with a spouse living in Mexico are more likely to return home, again showing that family decisions are related.

Finally, I estimate the probability of being allowed to immigrate legally, using a probit regression where the dependent variable is whether or not an individual was able to immigrate legally at the time of the survey. The results of this regression are shown in the third column of Table 3. People with more than 4 years of education are more likely to be allowed to immigrate legally. Older people and men are more likely to be granted legal status, as are people who have family in the U.S., which is expected due to the nature of U.S. immigration laws.

4.3 Internal Migration

In the model, individuals choose from a set of locations in Mexico and the United States. Internal migration is fairly common, as over 23% of the sample moves internally. There is the most movement in and out of Mexico City, which, even though it does not have the highest wages, is by far the largest city in Mexico. Mexico City has high out-migration rates because many people move there temporarily and eventually return home.

To study the determinants of location choices, I take four of the states with the most internal migrants in the MMP data (Guanajuato, Jalisco, Michoacań, and Veracruz) and analyze destination choices. For the most part, distance is the biggest determinant of migration decisions, as people move to fairly close locations. In Guanajuato, Jalisco, and Michoacán, 47%, 62%, and 55% of migrants moved to bordering states, respectively. This number is lower in Veracruz, where 18% of the moves are to bordering states. In all of these states, most remaining moves are to either high wage locations or to Mexico City. In Veracruz, a much higher percentage of people move to high wage locations than the migrants from the other states. This data shows that people are likely to move to their home location, to close-distance locations, and to high wage locations. The model accounts for these incentives for internal migration. The utility function includes a home preference and is a function of wages, explaining why people return home or move to high-wage locations. The distance between locations is included in the moving costs to account for the fact that many moves are to nearby locations.[12]

[12]The one part that is not explained well is the high number of moves to Mexico City, which has high in-

4.4 Border Enforcement

To measure border enforcement, I use data from the U.S. Customs and Border Protection (CBP) on the number of man-hours spent patrolling the border. CBP divides the U.S.-Mexico border into 9 different sectors, each of which gets a different allocation of resources each year. The sectors are San Diego and El Centro in California, Yuma and Tucson in Arizona, El Paso in New Mexico, and Marfa, Del Rio, Laredo, and the Rio Grande Valley in Texas. Figure 2 shows the number of man-hours spent patrolling each region of the border over time.[13] Relative to the levels observed today, border patrol was fairly low in the early 1980's. Enforcement was initially highest at San Diego and grew the fastest there. Enforcement also grew substantially at Tucson, although the growth started later than at San Diego. The other sector with significant growth was the Rio Grande Valley. In most of the other sectors, there was a small amount of growth in enforcement, mostly starting in the late 1990's.

Much of the variation in Figure 2 can be explained by changes in U.S. policy. The *Immigration Reform and Control Act* of 1986 (IRCA) called for increased enforcement along the U.S.-Mexico border. However, changes in enforcement were small until the early 1990's, when new policies further increased border patrol. In 1993, *Operation Hold the Line* increased enforcement at El Paso. There was a large growth in enforcement in 1994 in San Diego due to *Operation Gatekeeper*. The *Illegal Immigration Reform and Immigrant Responsibility Act* of 1996 allocated more resources to border enforcement.

Illegal immigrants surveyed in the MMP reported the closest city in Mexico to where they crossed the border. I use this information to match each individual to a border patrol sector.[14] Figure 3 shows the percent of illegal immigrants who cross the border at each crossing point in each year. Initially, the largest share of people crossed the border near San Diego. However, as enforcement there increased, fewer people crossed at San Diego. Before 1995, about 60% of illegal immigrants crossed the border at San Diego. This decreased to 35% between 1995 and 1999 and to 20% in the year 2000 and after. At the same time, the share of people crossing at Tucson increased, indicating that migrants shifted from crossing at San Diego to Tucson. I use this variation in behavior, combined with the changes in enforcement at each sector over time, to identify the effect of border enforcement on immigration decisions.

migration rates, yet is not always close to the starting location and has approximately average wage levels. This could be controlled for by using population size as part of the moving cost for internal migrants.

[13] The data reports the levels of patrol on a monthly basis. This graph shows the average for each year.

[14] This map from CBP shows how the border is divided: `http://www.cbp.gov/linkhandler/cgov/careers/customs_careers/border_careers/bp_agent/sectors_map.ctt/Sectors_Map.pdf`.

5. Estimation

I estimate the model in Section 3 using maximum likelihood. I assume that a person has 27 location choices, of which 23 are in Mexico and 4 are in the United States. For 22 of the 23 locations in Mexico, a location is defined as a state. The 23rd location in Mexico is all other states, which were combined because very few people in the data ever lived there.[15] There are four locations in the U.S.: California, Texas, Illinois, and all others. These three states are the ones where most migrants in the data move. Illegal immigrants moving to the U.S. also choose between the nine border patrol sectors. Therefore, an illegal immigrant has 36 choices in the U.S.- the four locations combined with the nine crossing points.

I define a time period as one year, and use a one-year discount rate of 0.95. I assume that people solve the model starting at age 17 and work until age 65.

To estimate the model, I assume perfect foresight over future wages and border enforcement. Since people are projecting beyond the year 2004, I do not have data on these factors for all years. I assume that wages and enforcement remain constant in the future.

Before estimating the model, I need to specify the wage distribution, moving costs, transitions into legal status, and the utility function.

5.1 Wages

When deciding where to live, a person considers his expected wage in all of his location choices. I use wage regressions to calculate these expected wages.

The MMP data records migrants' realized wages in the United States. Since each person has the option of moving within Mexico, I need to estimate wages in each Mexican state. I use data from Mexico's labor force survey to do this. Table 4 shows the average hourly wages in the U.S. and Mexico (in 2000 dollars), dividing the sample by education. There are large wage differentials between the 2 countries, which decrease with education.

I regress wages on education, gender, age, legal status, and whether or not a person has family living in the United States. I include the family variable as an indicator of network effects. Munshi (2003) finds that a Mexican immigrant living in the U.S. is more likely to be employed and to hold a higher paying nonagricultural job if his network is larger.

The results of this regression for U.S. wages are shown in the first column of Table 5. Wages increase with education, although there is no return to more than 11 years of education. Illegal immigrants earn less, and people with family in the U.S. earn

[15] The 10 states combined into this location are Baja California Sur, Campeche, Coahuila, Chiapas, Nayarit, Queretaro, Quintana Roo, Sonora, Tabasco, and Tamaulipas.

more.[16] Wages increase with age for people younger than 24, at which point they begin to decrease with age. The decline in wages with age is very small, averaging less than five cents per year. This is different that standard findings with regard to age and wages, as typically older people have more experience and therefore earn higher wages. However, in this case, many illegal immigrants work in agriculture or construction, occupations which require physical labor and therefore may place a premium on youth. In the data, 33% of the jobs are in agriculture, 36% are in manufacturing and construction, and 18% are in services. When I run separate wage regressions for each of these three main occupations, wages strongly decrease with age for agriculture, have a similar pattern to the overall wage regression for manufacturing, and have the standard concave shape for services.

The second column of Table 5 show the results of the wage regression for Mexican wages. The returns to education and age are much higher in Mexico than in the United States. Mexico is a less-developed country than the U.S., so there are fewer educated people, leading to strong returns to skills. Furthermore, since most immigrants are illegal, educated people do not have access to the full U.S. labor market and therefore may not be able to find jobs that use higher levels of education.

I use the results of these regressions to calculate an expected wage for each person in each location and year. For now, I assume that there is no wage variation, so each person is earning his expected wage in his current location.[17]

The U.S. wage data is potentially biased due to self-selection, as I only observe wages for people who made the decision to immigrate. The data shows that immigrants are selected on education and age. Dahl (2002) develops an econometric methodology to account for this self-selection problem, which he applies to data on state to state migration in the United States. He finds evidence that educated people select into states with high returns to education. This upwardly biases the OLS estimates of returns to education in state-specific labor markets. In this paper, the bias comes from the binary decision on whether or not to migrate, so I can use the Heckman two-step estimator to correct the U.S. wage estimates.

5.2 Moving Costs

The cost of moving depends on whether a person can immigrate legally, which locations he is moving between, and his network in the U.S. For illegal immigrants moving to the U.S., the cost of moving depends on border enforcement. To measure

[16] One problem with this specification is that returns to education should vary for legal and illegal immigrants. However, because there are so few wage observations for legal immigrants, it is hard to estimate the returns to education for this group.

[17] Potentially, a person's income draw when in the U.S. could affect whether or not he stays. In future work, I can relax this assumption and allow for individual-level variation in wage draws.

enforcement, I use CBP data on the number of man-hours spent patrolling a given sector of the border.

Networks, at both the state and individual level, can affect the cost of moving to the United States. Networks are defined as the people that an individual knows who are already living in the United States. Colussi (2006) finds that networks increase the probability that a person will immigrate from Mexico to the United States.[18] Empirical evidence shows that migration rates vary across states, meaning that people from high-migration states have larger networks. I exploit differences in state level immigration patterns, which have been well-documented empirically, to measure a person's network. I use the distance to the railroad as a proxy for regional network effects.[19] When immigration from Mexico to the U.S. began in the early 1900's, U.S. employers used railroads to transport labor across the border, meaning that the first migrants came from communities located near the railroad (Durand, Massey, and Zenteno, 2001). These communities still have the highest immigration rates today.[20] To account for individual networks, I control for whether a person currently has a family member living in the U.S.

I control for the distance between locations. The distances were calculated as the driving distances between state capitals. When a person is moving to the U.S. illegally, I calculate the distance from a state in Mexico to a border crossing point plus the distance from the border crossing point to the location in the U.S.

Empirical evidence shows that younger people are more likely to immigrate. One explanation for this is that younger people have more time to benefit from higher wages. The model in this paper accounts for this explanation, as the model is dynamic, has a finite horizon, and age is a state variable. In addition, wages increase with age in Mexico and are fairly constant with age in the U.S., so younger people have a larger wage differential. However, there could be other factors that make younger people more likely to immigrate. For this reason, I include age in the moving cost. This will capture other effects of age on immigration that are not accounted for in the model or the wage distribution. I also control for education in the moving cost when moving to the U.S.[21]

Recall from Section 3.1 that $c_t(\cdot)$ is the moving cost function. This function de-

[18] Massey and Espinosa (1997) and Curran and Rivero-Fuentes (2003) also find that networks affect immigration decisions.

[19] I thank Craig McIntosh for providing the railroad data.

[20] In 1992, the 3 states with the largest share of all migrants were Jalisco, Michoacán, and Guanajuato (Woodruff and Zenteno, 2007), which are in the west-central region of Mexico. These states are close to rail lines, as Jalisco, Michoacán, and Guanajuato are 21, 28, and 26 miles from the railroad, respectively, compared to an average of 147 miles over all Mexican states.

[21] Education could also be included in the moving cost for internal and return moves. This will be included in future work.

pends on a person's legal status and on what locations he is moving between:

$$c_t(\ell_1, \ell_2, z_t, X_t) = \begin{cases} c_t^1(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_M, \ell_2 \in J_U, z_t = 1 \\ c_t^2(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_M, \ell_2 \in J_U \times C, z_t = 2 \\ c_t^3(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_U, \ell_2 \in J_M \\ c_t^4(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_M, \ell_2 \in J_M \end{cases}$$

The moving cost is given by $c_t^1(\cdot)$ for legal immigrants moving to the U.S., $c_t^2(\cdot)$ for illegal immigrants moving to the U.S., $c_t^3(\cdot)$ for return migrants, and $c_t^4(\cdot)$ for internal migrants. In the function $c_t^2(\cdot)$, the location ℓ_2 includes both a location in the U.S. and a border crossing point, as the moving cost for illegal immigrants depends on both of these factors. In this case $\ell_2 = (j \in J_{US}, k \in C)$. I define each of the moving cost functions as follows:

$$\begin{aligned} c_t^1(\ell_1, \ell_2, X_t) &= \lambda_1 + \lambda_2 d(\ell_1, \ell_2) + \lambda_3 rr(\ell_1) + \lambda_6 fam + \lambda_7 age + \sum_{k=1}^{N_e} e_k educ_k \\ c_t^2(\ell_1, \ell_2, X_t) &= \lambda_1 + \lambda_2 d(\ell_1, \ell_2) + \lambda_3 rr(\ell_1) + \lambda_6 fam + \lambda_7 age + \sum_{k=1}^{N_e} e_k educ_k + \lambda_8 b_{kt} + \lambda_k^b \\ c_t^3(\ell_1, \ell_2, X_t) &= \lambda_4 + \lambda_2 d(\ell_1, \ell_2) + \lambda_7 age \\ c_t^4(\ell_1, \ell_2, X_t) &= \lambda_5 + \lambda_2 d(\ell_1, \ell_2) + \lambda_7 age \end{aligned}$$

The cost of moving includes a fixed cost and depends on the distance between locations, which is written as $d(\ell_1, \ell_2)$. The fixed cost depends on whether a person is moving to the U.S. (λ_1), back to Mexico (λ_4), or within Mexico (λ_5). If moving to the U.S., the distance from a location to the railroad (denoted as $rr(\ell_1)$) affects the moving cost. The dummy variable fam indicates whether a person has family living in the United States. The moving cost increases by λ_6 if a person does not have family living in the U.S. The parameter λ_7 is the effect of age on moving costs, which I assume enters linearly. The term b_{kt} is border enforcement at crossing point k at time t, and λ_8 is the effect of border enforcement on moving cost. Each border crossing point has its own fixed cost, denoted as λ_k^b. Some of the border crossing points consistently have low enforcement, yet few people choose to cross there. I assume that there are other reasons, constant across time, that account for this trend, such as being in a desert where it is dangerous to cross. The estimated fixed costs account for these factors. For people moving to the U.S., I allow the moving cost to depend on education. I estimate an extra fixed cost for each education level. The term e_k is the estimated fixed cost for education group k. The term $educ_k$ is a dummy variable that equals 1 if a person is in education group k.

5.3 Transitions between Legal Status

There are two main pathways by which a person can become a legal immigrant. The first is by getting a visa, which can come through a family member who is an American citizen or through a work visa. Most Mexicans who are granted visas do so through family members. The other pathway is through an amnesty. In 1986, the U.S. government granted legal status to illegal immigrants living in the U.S. who met certain criteria. Although this has not happened since 1986, a similar policy has been considered recently.

In the model, I assume that people do not know whether they will be able to legally immigrate to the U.S. in the future. However, they do know the probability that they will be able to immigrate legally. I estimate the probability that a person switches from illegal to legal status, using a probit regression which controls for education, family networks, gender, and location. The policy change in 1986 granted many illegal immigrants legal status. I include a dummy variable for the years around that policy change to allow for the large growth in legalization at that time. I interact this variable with a dummy variable that indicates whether or not a person is living in the U.S., as the amnesty only applied to people who were in the U.S. at the time.

The results of this regression, shown in Table 6, indicate that having family in the U.S. and living in the U.S. are the biggest predictors of transitioning from illegal to legal status. Many people transitioned to legal status around the time that IRCA was implemented. I use the results of this regression to impute a probability of switching states for each individual. I assume that policies such as IRCA are unanticipated. People could only be legalized under IRCA if they had lived in the U.S. continuously since 1982. Therefore, this policy would only affect immigration decisions if it was anticipated it 4-5 years prior to implementation, making this assumption reasonable.

5.4 Utility Function

The utility function depends on a person's wage, which is a deterministic function of characteristics, legal status, and location, as explained in Section 5.1. It also depends on whether a person is living at his home location. In addition, for married people, utility depends on whether a person is at the same location as his spouse. To simplify computation, I assume that utility depends on whether they are living in the same country. I write the utility function as

$$u(\ell_t, X_t, z_t, \ell_t^s) = \begin{cases} \alpha_w w(X_t, z_t, \ell_t) + \alpha_H \mathbb{1}(\ell_t = H) + \alpha_S & \text{if } \ell_t \in J_M \text{ and } \ell_t^s \in J_M \\ \alpha_w w(X_t, z_t, \ell_t) + \alpha_H \mathbb{1}(\ell_t = H) + \alpha_S & \text{if } \ell_t \in J_U \text{ and } \ell_t^s \in J_U \\ \alpha_w w(X_t, z_t, \ell_t) + \alpha_H \mathbb{1}(\ell_t = H) & \text{if } \ell_t \in J_U \text{ and } \ell_t^s \in J_M \\ \alpha_w w(X_t, z_t, \ell_t) + \alpha_H \mathbb{1}(\ell_t = H) & \text{if } \ell_t \in J_M \text{ and } \ell_t^s \in J_U \end{cases}$$

Utility depends on a person's wage, location ℓ_t, spouse's location ℓ_t^s (if married), and characteristics X_t, which affect utility through the home location H. I assume that utility is linear in a person's wage, where α_w is a term to be estimated. In the utility function, $\mathbb{1}(\cdot)$ is an indicator function that equals 1 if the term in parentheses is true and 0 otherwise. A person's utility increases by the amount α_H if he is living at his home location, which is defined as the state in which he was born. A person's utility decreases by α_S if he is not in the same country as his spouse.

5.5 Likelihood Function

I estimate the model using maximum likelihood. Denote a person's marital status as m, where $m = 1$ is a primary mover and $m = 2$ is a secondary mover.

Denote the set of parameters to be estimated as θ, where θ includes the utility and moving cost parameters. For each individual, I observe a history of location choices $H = \{\ell_0, \ell_1, ..., \ell_T\}$. The first location ($\ell_0$), his location at age 17, is taken as exogenous. The rest of the locations are a person's choices. A person's location choice in one time period is his initial location at the start of the next period. In addition, the choices of a person's spouse are part of his state space. For the primary mover, his spouse's location in the previous period is in his state space. For the secondary mover, the primary mover's location in the current period is part of her state space.

Denote $P_t^m(\cdot)$ as the choice probability for a person with marital status m. These choice probabilities were defined in equations (6) and (3) in section 3 for primary and secondary movers, respectively.

Denote the probability of seeing an observed history for household i as $\chi(H_i^1, H_i^2, \theta)$, where H_i^1 and H_i^2 are the location histories of the primary and secondary mover, respectively. Then

$$
\begin{aligned}
\chi(H_i^1, H_i^2, \theta) \quad = \quad & P_1^1(\ell_{i1}^1 | \ell_{i0}^1, \Delta_{i1}^1, \ell_{i0}^2, \theta) \times P_1^2(\ell_{i1}^2 | \ell_{i0}^2, \Delta_{i1}^2, \ell_{i1}^1, \theta) \\
\times \quad & P_2^1(\ell_{i2}^1 | \ell_{i1}^1, \Delta_{i2}^1, \ell_{i1}^2, \theta) \times P_2^2(\ell_{i1}^2 | \ell_{i1}^2, \Delta_{i2}^2, \ell_{i2}^1, \theta) \\
\times \quad & ... \\
\times \quad & P_T^1(\ell_{iT}^1 | \ell_{i,T-1}^1, \Delta_{iT}^1, \ell_{i,T-1}^2, \theta) \times P_T^2(\ell_{iT}^2 | \ell_{i,T-1}^2, \Delta_{iT}^2, \ell_{iT}^1, \theta)
\end{aligned}
$$

In each period, I calculate the probability that the primary and secondary mover make a given decision. The probability of seeing an observed history for a household is the product of these probabilities in each time period. The recursive structure here is important, as a choice at time t becomes part of the state space at time $t + 1$. In addition, the choices of one's spouse enter into an individual's state space. The log-likelihood function is the sum, over households, of the log of the probability of seeing each history:

$$L(\theta) = \sum_i \log\left(\chi(H_i^1, H_i^2, \theta)\right)$$

6. Results

The parameter estimates are reported in Table 7. The utility parameters all have the expected sign and are statistically significant. These estimates indicate that people prefer to earn higher wages, people prefer to live at their home location, and that living in the same location as one's spouse increases utility.

The first component of the moving cost is the fixed costs of moving. I estimate a separate fixed cost if moving to the U.S., returning to Mexico, or moving internally. The fixed cost of returning to Mexico is lowest.

For illegal immigrants, I find that moving costs increase with border enforcement. I estimate a separate fixed cost for each border crossing point. The crossing points with low levels of enforcement, but where people do not cross, have high fixed costs. San Diego and Tucson, where most people cross but also have the highest enforcement, have the lowest fixed costs.

I estimate four distance parameters, assuming that distance can affect moves in each direction in different ways. I also separate the distance parameter for legal and illegal immigrants moving to the United States. For legal immigrants, the distance is measured as the distance between locations. For illegal immigrants, it is the distance from the original location to the border crossing point plus the distance from the crossing point to the location in the United States. I estimate a separate distance parameter for illegal and legal immigrants because the distances are measured differently. Three of the four distance parameters are positive, implying that the moving cost increases with distance. The fourth, which is for return migration, is negative, meaning that the return migration costs are lowest for people traveling the furthest distances. This is counterintuitive, and implies that people are more likely to return migrate if they are living far from Mexico or if they are going to locations in Mexico that are far from the U.S. border.

Networks affect moving costs through the distance to the railroad and based on whether a person has family living in the United States. These both move in the expected direction, in that larger networks decrease moving costs. In the estimation, having a family member in the U.S. affects not only the moving cost but also a person's wage in the United States. Because the estimated moving cost is lower for people with family networks, family networks affect immigration decisions beyond the wage effect.

Moving costs increase with age, which implies that standard human capital theory does not fully explain why younger people are more likely to immigrate. Other factors outside the model make younger people more likely to move.

I estimated a separate fixed cost of moving to the U.S. based on education level. I divided the sample into five education groups and estimated four parameters, where people with 13 or more years of education were the excluded group. The costs of moving are lowest for people with 0-8 years of education. These people also have the largest wage differentials, implying that the wage differentials do not fully explain why people with less education are the most likely to immigrate.

Table 8 shows the model fit. Overall, the model fits the data fairly well. I split the sample based on age, education, and marital status. For people living in Mexico, I compare the model's predicted immigration rates with those in the data. For people living in the U.S. at the start of a period, I compare the probability that they stay in the U.S. with the observed choices. The model predicts a sharper drop in migration rates with age than what is observed in the data. Also, the model predicts that older people will be more likely to remain in the U.S., whereas in the data older people are more likely to return to Mexico. In the estimation, the moving cost increases with age for both Mexico to U.S. and return migration. However, the effect of age on moving cost could be different for initial and return migration. When splitting the sample by education, the model fits Mexico to U.S. immigration rates fairly well. It does not fit return migration rates as well. The model underpredicts immigration rates for primary and secondary movers. I assumed that the disutility of being separated from one's spouse is the same, regardless of where the individual lives. However, it could be that the disutility of being separated from one's spouse is different if living alone in the U.S. or alone in Mexico. The return migration rates for primary movers match the data well, but are too high for secondary movers. In the data, most secondary movers who are in the U.S. do not move. For single people, the model fits the data fairly well.

To understand how different factors affect immigration rates in the model, I calculate migration probabilities for individuals with different characteristics. Figure 4 shows the probability that a person who is living in Guanajuato moves to the U.S. in a given year. I vary the wage differentials due to education and age. Migration rates decrease with age. The wage differentials are highest for people with the least education, causing them to have much higher immigration rates than people in high education groups, especially at younger ages. In Figure 5, I vary whether or not a person has family living in the United States. In this case, I assume that he is in the low-wage, high-wage-differential group. Family networks cause large increases in migration rates. This is caused by two factors: people with family networks earn higher wages in the U.S. and have lower moving costs. I decomposed this difference and found that most of it is due to the moving cost.

7. Counterfactuals

7.1 Annual Migration Rates

I calculate how changes in Mexican wages and U.S. policy affect annual immigration rates. Table 9 shows immigration rates for a 25 year-old primary mover with 0-4 years of education who is living in Guanajuato, which is his home location. I calculate immigration rates for this person with and without a family network. As in Figure 5, family networks cause a large increase in immigration rates. First I calculate how changes in Mexican wages affect immigration, assuming that wages in each state grow by 10%. I find that this reduces migration rates. Next, I calculate how increased enforcement affects immigration, assuming that the man-hours allocated to enforcement at each crossing point increase by 50%. This also reduces immigration rates. In the last row of Table 9, I assume that the U.S. government eliminates legal immigration. In the model, this would affect transition probabilities, as there would now be no probability of switching from illegal to legal status. This has two effects on illegal immigration. First, if a person thinks that there is a high chance that he will become a legal immigrant in future periods, he has an incentive to wait to move in order to pay the lower moving costs. If there is no more legal immigration, this waiting incentive no longer exists, so immigration rates in the current period increase. Secondly, wages are higher for legal immigrants. If there is no more legal immigration, then the value of living in the U.S. decreases, lowering immigration rates. The last row of Table 9 shows the results of this exercise. Immigration rates decrease, indicating that the wage effect dominates.

Changes in wages and U.S. policy also affect return migration rates. Table 10 shows the probability that a person living in the U.S. will return to Mexico in a given year.[22] I calculate this probability for a primary mover whose spouse is in the U.S. and whose spouse is in Mexico. If a person's spouse is living in Mexico, he is more likely to return home. This is because his utility will increase if he lives at the same location as his spouse. Higher Mexican wages increase return migration rates by increasing the value of living in Mexico. Increased enforcement reduces return migration rates. As enforcement increases, current illegal migrants become reluctant to return home, knowing that it will be harder to re-enter the U.S. in the future. In the last row, I calculate immigration rates if there is no more legal immigration. As with Mexico to U.S. immigration, there are two effects. The expected cost of moving to the U.S. in future periods increases because there is no chance paying the lower moving costs associated with legal immigration. This decreases return migration. Second, since legal immigrants earn higher wages, the value of living in the U.S. decreases. This increases return migration. As before, the wage effect dominates, although the overall

[22] This is for a person whose home state is Guanajuato, is 25 years old, and has family living in the U.S.

effect is small.

The results in Tables 9 and 10 show that an increase in Mexican wages has two effects: people are less likely to move, and of those that move, they are more likely to return to Mexico. This second effect means that durations of stays in the U.S. will be shorter. Overall, increased Mexican wages reduce immigration, as fewer people will move and they will stay in the U.S. for shorter periods of time. There are also two effects of increased border enforcement: people are less likely to move, and, conditional on migrating, are less likely to return home. This means the duration of stays in the U.S. is longer. Therefore, based on this preliminary analysis, the overall effect of increased enforcement on immigration is ambiguous. In the next section, I simulate behavior over a lifetime, enabling me to calculate the overall effect.

7.2 Lifetime Behavior

I simulate behavior over a lifetime in three scenarios: a baseline case, a 10% increase in Mexican wages, and a 50% increase in man-hours patrolling the border. The results are shown in Table 11. In each case, I report the percent of the sample that moves to the U.S., the average number of moves to the U.S. per migrant, the average number of years spend living in the U.S. per move, and the average number of years a person lives in the U.S. over a lifetime. The baseline case shows that a higher fraction of the sample moves in the simulation than in the data. In addition, the number of moves per migrant is lower than in the data. I believe that this could be fixed by adding mover-stayer types to the model.[23]

7.2.1 Growth in Mexican Wages

Increases in Mexican wages reduce illegal immigration in the model. I assume that Mexican wages grow by 10% in all states and that U.S. wages remain constant. This reduces the average number of years that a person lives in the United States over a lifetime. Table 11 shows that 5.4% fewer people move to the U.S. than in the baseline case. The number of moves per migrant stays approximately constant. Of those that move, the duration of each trip decreases by 6.6%. This follows the results in Table 10, which showed that return migration rates increase with Mexican wages. These effects combine to decrease the average number of years that a person lives in the U.S. by 11.6%.

7.2.2 Border Enforcement

The U.S. government is considering further increases in border enforcement. I assume that the man-hours allocated to enforcement uniformly increase by 50%, which raises

[23] This will be included in future work.

the moving cost. Table 11 shows that this has three effects on illegal immigration. As enforcement increases, 8.3% fewer people move due to the higher moving costs. Furthermore, each migrant moves to the U.S. fewer times. These two effects reduce illegal immigration. However, the third effect moves in the opposite direction. Of those that move, the duration of each stay in the U.S. increases by 3.3%, following the lower return migration rates in Table 10. Overall, this results in a 9.3% reduction in the number of years that the average person lives in the U.S.

In the previous exercise, I assumed that enforcement increases by 50% at each border patrol sector. In comparison to past work on this topic, my model can be used to optimally allocate border enforcement. I again assume a 50% total increase in enforcement, but I allocate the extra resources in a way to minimize illegal immigration rates. If the government aims to minimize illegal immigration, the solution to the static problem indicates that the cost of crossing at each sector of the border should be equal. Due to the wide variation in the estimated fixed costs across border patrol sectors, it is not possible to reach this point with only a 50% increase in enforcement. To get closest to this point, the extra resources should be allocated to two sectors of the border, San Diego and Tucson, which have the lowest fixed costs of crossing. These two points also have the highest enforcement levels, but even after accounting for the effects of enforcement, the costs of crossing there are still lowest. The last row of Table 11 shows the results of this simulation. In this case, 17.8% fewer people move than in the baseline scenario. This is more than double the effect than when there was a uniform increase in enforcement. As before, each migrant moves fewer times. The number of moves per migrant is 8.8% lower than in the baseline case. Again, the duration of each stay in the U.S. is lower than in the baseline case. Overall, this increase in enforcement reduces the average amount of time a person lives in the U.S. by 23%, which is more than double the effect than when enforcement increased uniformly. This shows that the effect of increased enforcement depends on on the allocation of the extra resources.

8. Conclusion

In this paper, I estimate a discrete choice dynamic programming model where people pick from a set of locations in the U.S. and Mexico in each period. I use this model to understand how wage differentials and U.S. border enforcement affect an individual's immigration decisions. When deciding where to live, individuals take into account the current and future benefit of living in each location, understanding that immigration decisions may not be permanent. This is important because of the empirical evidence that people move multiple times over the course of a lifetime. In addition, wages and enforcement affects both initial and return migration decisions.

To understand how enforcement affects illegal immigration, it is necessary to use a model that allows for both of these effects.

I allow for differences in the model according to whether a person can immigrate to the U.S. legally. For illegal immigrants, the moving cost depends on U.S. border enforcement. Border enforcement is measured using data from U.S. Customs and Border Protection on the number of man-hours spent patrolling different regions of the border at each point in time. I use this cross sectional and time series variation in enforcement, combined with individual decisions on where to cross the border, to identify the effects of enforcement on immigration decisions. Initially, most migrants crossed the border at San Diego. As enforcement at San Diego increased, migrants shifted to new crossing points. Using overall enforcement levels, instead of the regional levels combined with crossing point decisions, misses this effect.

Previous empirical research on U.S.-Mexico immigration shows that family decisions are related. For example, a woman is much more likely to move to the U.S. if her husband is already there. To model immigration decisions, it is important to account for these factors. However, most past structural work on this topic does not allow for the decisions of members of the same household to be related. I allow for a person's utility to depend on the location of his spouse. I model decisions in a two-step process, where individuals in a household make decisions sequentially. By allowing the decisions of a household to be related, I can better understand immigration behavior.

After estimating the model I find that increases in Mexican wages reduce immigration from Mexico to the U.S. and increase return migration rates. Simulations show that a 10% increase in Mexican wages reduces the average number of years that a person lives in the U.S. over a lifetime by 11.6%. Increases in border enforcement decrease both immigration and return migration, with the latter effect occurring because, as enforcement increases, individuals living in the U.S. expect that it will be harder to reenter the country in the future. Overall, a uniform 50% increase in enforcement would reduce the amount of time that individuals in the sample spent in the U.S. over the course of a lifetime by approximately 9.3%. If instead the same increase in enforcement were allocated along in the border in a way to minimize immigration rates, the number of years that the average person in the sample lived in the U.S. would drop by 23%. This shows that the effects of enforcement are very dependent on the allocation of the extra resources.

These results have important implications. The U.S. government is considering increasing border enforcement in the future. I find that this will reduce illegal immigration. Furthermore, my model shows that the effects of increased enforcement depend on the allocation of resources along the border. Over the past 20 years, enforcement levels have increased substantially, and the growth in enforcement has been concentrated at certain sectors of the border. If the goal of the U.S. government is to reduce illegal immigration, then my model suggests that this has been the correct strategy.

Furthermore, if the U.S. increases enforcement in the future, my results indicate that they should continue to follow this pattern.

My results imply that increases in Mexican wages reduce illegal immigration. In the paper, I simulate the effects of a 10% growth in Mexican wages, finding that it significantly reduces the amount of immigration, even though there is still a large U.S.-Mexico wage gap. Because of the large moving costs and a strong preference for living at one's home location, illegal immigration will decrease substantially as the wage differential is reduced. Furthermore, wage growth does not have to be uniformly distributed in Mexico to affect immigration. Empirical evidence shows that wage growth has not been uniform and that regional wage disparities within Mexico have grown, particularly since NAFTA. The areas with the most growth are the ones with access to foreign trade and investment. My model allows for internal migration as well as moves to the United States. Wage growth in individual regions will reduce illegal immigration, as people can choose to move there instead of to the United States. In future work, I can use my model to understand how this will affect illegal immigration.

There are some improvements that could improve the fit of the model. One is to add unobserved heterogeneity into the moving costs. Another improvement would be to allow for individual variation in wage draws. People who get high wage draws in the U.S. should be less likely to return migrate. I can add this to the estimation to improve the model's ability to predict behavior. In addition, the estimated wages in the U.S. do not allow for selection, possibly causing biased estimates of the wage regression. I can correct this bias by controlling for selection.

This paper studies immigration in a partial equilibrium framework, not allowing for general equilibrium effects. However, increases in immigration could drive down wages in the U.S. or cause higher wages in Mexico. This is an important question that I plan to address in future work. This paper is a first step in that direction and helps to provide the foundation to do such an analysis.

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Table 1: Sample Characteristics

	Internal Movers	Moves to U.S.	Moves Internally and to the U.S.	Non-Migrant	Legal Immigrant
Percent that is Male	56.7%	85.8%	92.5%	41.2%	82.0%
Percent that is Married	83.6%	83.5%	74.7%	89.9%	72.0%
Average Age	29.4	30.3	31.3	30.5	29.9
0-4 Years Education	11.0%	15.9%	9.1%	12.4%	8.3%
5-8 Years Education	32.1%	37.2%	42.3%	33.5%	41.1%
9-11 Years Education	30.7%	31.6%	30.8%	32.0%	27.6%
12 Years Education	15.2%	10.9%	9.9%	13.7%	14.7%
13+ Years Education	11.0%	4.4%	7.9%	8.4%	8.3%
Number of Observations	1,253	1,272	253	5,781	421

Table 2: Number of Moves to the U.S.

Years of Education	Men	Women	Age	Men	Women
0-4	3.9	2.0	≤30	1.9	1.4
5-8	2.7	1.7	31-40	2.8	1.8
9	1.9	1.5	41-50	3.4	2.1
12	1.8	1.4	51+	4.2	2.2
13+	2.0	1.9			

Table 3: Probability of Moving

	Moves to U.S.	Return Migrate	Legal
5-8 Years Education	0.06**	0.02	0.40***
	(0.03)	(0.05)	(0.09)
9-11 Years Education	-0.01	-0.12**	0.27***
	(0.03)	(0.06)	(0.09)
12 Years Education	-0.10**	-0.06	0.36***
	(0.04)	(0.07)	(0.11)
13+ Years Education	-0.33***	-0.004	0.17
	(0.04)	(0.08)	(0.12)
Age[a]	-1.03***	-0.52	0.28***
	(0.17)	(0.35)	(0.06)
Age-squared	0.14***	0.10	-
	(0.02)	(0.06)	
Family in U.S.	0.34***	-0.17***	0.70***
	(0.02)	(0.03)	(0.05)
Male	0.89***	-0.01	0.56***
	(0.03)	(0.06)	(0.06)
Legal	1.06***	-0.88***	-
	(0.05)	(0.05)	
Married	-0.13***	-1.11***	-
	(0.02)	(0.08)	
Spouse in U.S.	0.81***	-	-
	(0.05)		
Spouse in Mexico	-	1.71***	-
		(0.09)	
Moved to U.S. Before	0.72***	-	-
	(0.03)		
Constant	-0.98***	-0.16	-2.85***
	(0.23)	(0.47)	(0.21)
Time Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	No	No
Pseudo R-squared	0.19	0.18	0.16

Standard errors in parentheses

*** .01 significance, ** .05 significance, * .10 significance

[a] Age divided by 10

Table 4: Average Wages

Years of Education	Mexico	U.S.
0-4	1.59	5.64
5-8	2.01	7.20
9-11	2.33	7.22
12	2.94	7.25
13+	4.96	7.72

Hourly wages, in 2000 dollars.

Table 5: Wage Regressions

	In the U.S.	In Mexico
5-8 years education	0.18**	0.44***
	(0.08)	(0.01)
9-11 years education	0.37***	0.77***
	(0.10)	(0.01)
12 years education	0.35**	1.17***
	(0.14)	(0.01)
13+ years education	0.37**	2.30***
	(0.15)	(0.01)
Illegal Immigrant	-1.16***	-
	(0.07)	
Age[a]	0.38**	1.24***
	(0.16)	(0.01)
Age-squared	-0.08***	-0.13***
	(0.02)	(0.001)
Male	0.72***	0.74***
	(0.08)	(0.003)
Family in U.S.	0.28***	-
	(0.08)	
Constant	6.10***	-2.42***
	(0.42)	(0.01)
Time Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
R-squared	0.11	0.11
Number of Observations	7,632	3,234,006

Standard errors in parentheses

*** .01 significance, ** .05 significance, * .10 significance

[a] Age divided by 10

Table 6: Transitions into Legal Status

5-8 Years Education	0.23***
	(0.08)
9-11 Years Education	0.17**
	(0.09)
12 Years Education	0.26***
	(0.10)
13+ Years Education	0.14
	(0.11)
Family	0.35***
	(0.05)
Male	0.19***
	(0.06)
In U.S.	.98***
	(0.06)
IRCA	0.48***
	(0.07)
IRCA*in U.S.	0.83***
	(0.09)
Constant	-3.69***
	(0.09)
Pseudo R-squared	0.35

Standard errors in parentheses

*** .01 significance, ** .05 significance, * .10 significance

Table 7: Parameter Estimates

Utility		Fixed Costs of Moving	
Wage Term	0.084	Mexico to U.S.	5.82
	(0.0027)		(0.0077)
Home Bias	0.33	U.S. to Mexico	2.64
	(0.0055)		(0.19)
With Family	0.19	Internal Move	4.52
	(0.012)		(0.047)
Distance Parameters in Moving Cost		Other Components of Moving Cost	
Illegal	1.05	Enforcement	0.023
	(0.013)		(0.0057)
Legal	0.85	Distance to Railroad	0.071
	(0.10)		(0.0088)
Internal	0.43	No Family in U.S.	0.61
	(0.041)		(0.036)
Return	-0.82	Age Parameter	0.023
	(0.053)		(0.0017)
Education in Moving Cost		Crossing Point Fixed Costs	
0-4 Years Education	-0.60	Del Rio, TX	0.89
	(0.09)		(0.22)
5-8 Years Education	-0.66	El Paso, TX	0.033
	(0.08)		(0.19)
9-11 Years Education	-0.38	San Diego, CA	-2.44
	(0.08)		(0.17)
12 Years Education	-0.17	Yuma, AZ	0.16
	(0.09)		(0.25)
		Laredo, TX	0.73
			(0.20)
		Rio Grande Valley, TX	0.75
			(0.19)
		Tucson, AZ	-1.11
			(0.18)
		Marfa, TX	2.24
			(0.33)
		El Centro, TX	-0.28
			(0.20)
Log Likelihood	-43,957.0		

Distance measured in 1000's of miles, enforcement measured in 10,000 man-hours.

Standard errors in parentheses.

Table 8: Model Fit

Probability of Living in the U.S.				
Age	Initially in Mexico		Initially in the U.S.	
	Model	Data	Model	Data
17-25	3.28%	3.54%	78.24%	80.30%
26-35	2.26%	3.17%	79.62%	80.30%
36+	1.11%	2.86%	81.11%	71.56%
Years of Education	Initially in Mexico		Initially in the U.S.	
	Model	Data	Model	Data
0-4	2.82%	3.57%	79.04%	74.52%
5-8	3.54%	4.46%	78.32%	78.53%
9-11	2.82%	3.30%	79.74%	81.84%
12	2.49%	2.48%	79.28%	83.32%
13+	1.83%	1.58%	77.65%	83.82%
Marital Status	Initially in Mexico		Initially in the U.S.	
	Model	Data	Model	Data
Primary Mover	2.03%	3.79%	77.51%	74.05%
Secondary Mover	3.13%	3.44%	78.86%	96.81%
Single	3.46%	3.13%	80.27%	81.77%

Table 9: Illegal Immigration Rates (Annual)

	Family in U.S.	No Family in U.S.
Baseline	3.66%	1.46%
Mexican wages up 10%	3.37%	1.35%
Enforcement up 50%	3.12%	1.24%
Never Legal	3.60%	1.44%

Illegal immigration probabilities for a 25 year old with 0-4 years of education who is a primary mover and is living in Guanajuato.

Table 10: Return Migration Rates (Annual)

	Spouse in Mexico	Spouse in US
Baseline	17.41%	14.20%
Mexican wages up 10%	18.05%	14.78%
Enforcement up 50%	16.93%	13.61%
Never Legal	17.44%	14.22%

Return migration probabilities for a 25 year old illegal immigrant with 0-4 years of education, whose home location is Guanajuato, is a primary mover, and has family in the U.S.

Table 11: Lifetime Behavior

	Percent that move	Moves per migrant	Years per Move	Years in US per person
Baseline	41.75%	1.70	6.1	4.3
10% increase in Mexican wages	39.5%	1.70	5.7	3.8
50% increase in enforcement	38.3%	1.62	6.3	3.9
50% increase in enforcement (efficient)	34.31%	1.55	6.24	3.32

Figure 1: Timing of Decisions

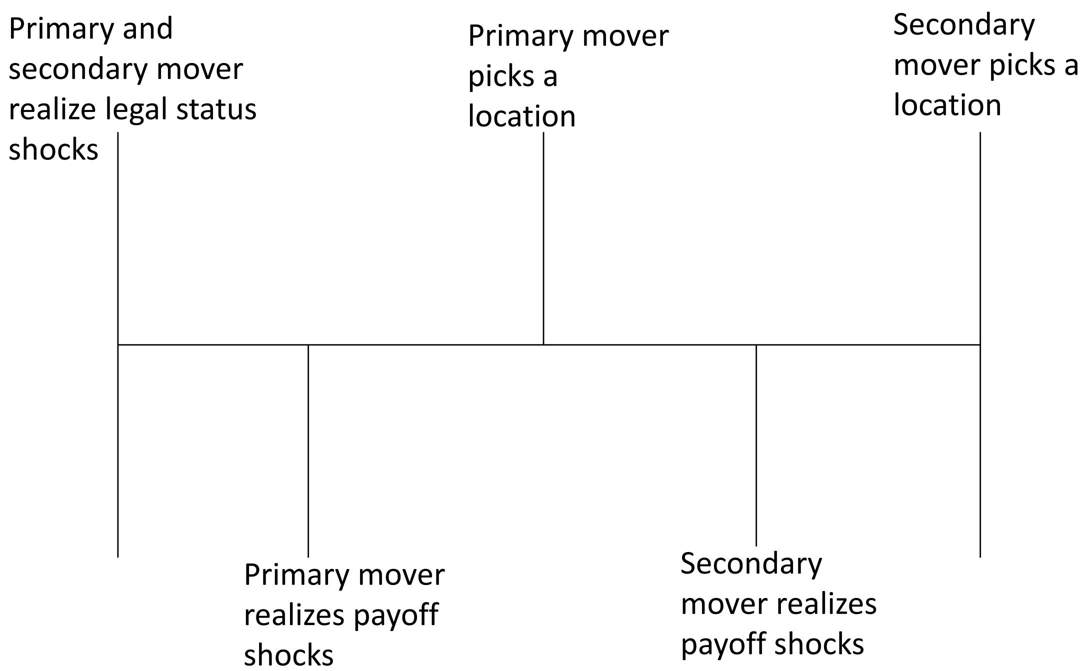

Figure 2: Hours Patrolling the Border

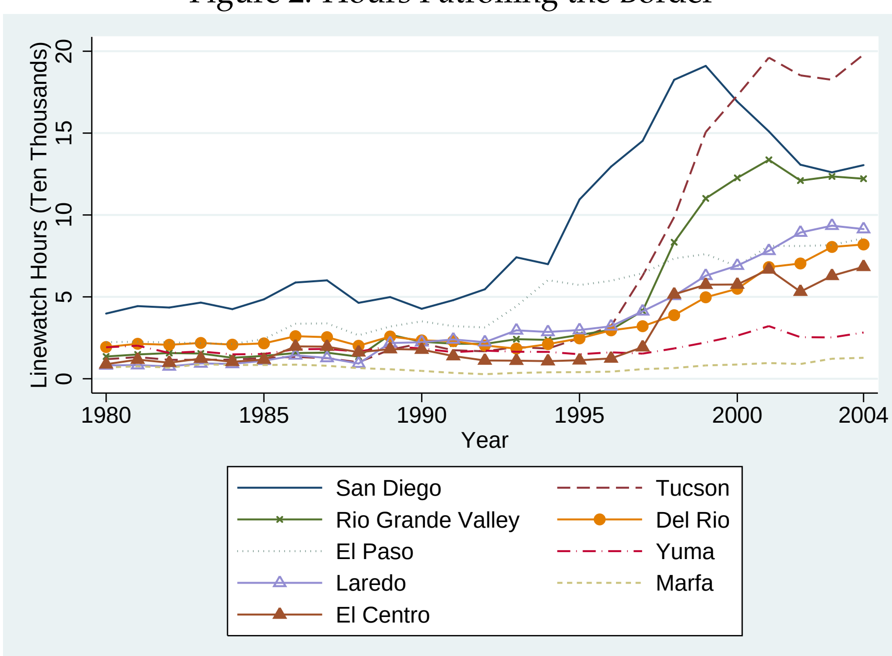

Figure 3: Border Crossing Locations (MMP)

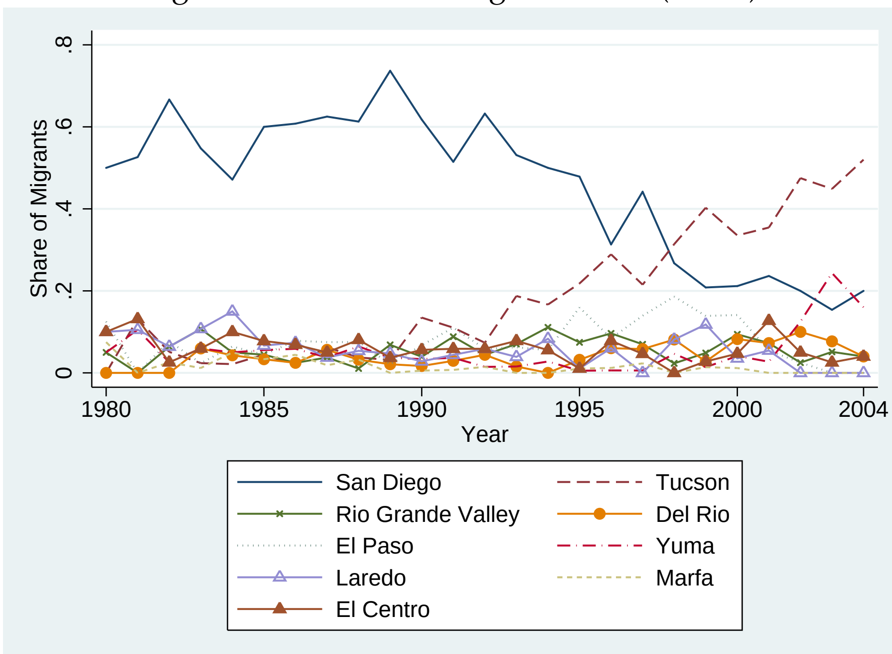

Figure 4: Annual Migration Rates (Education)

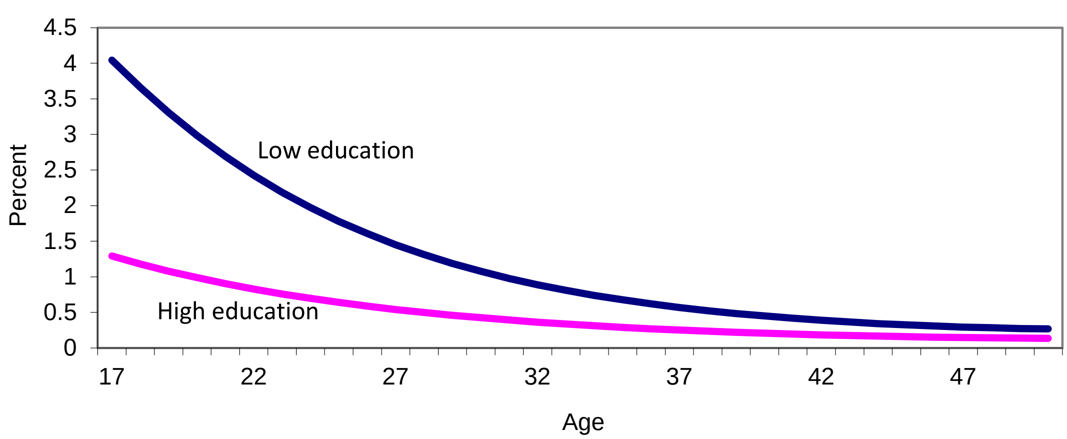

Figure 5: Annual Migration Rates (Family)