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# Mexico-U.S. Immigration: Effects of Wages and Border Enforcement

Rebecca Lessem*

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**Abstract**

I study how relative wages and U.S. border enforcement affect immigration from Mexico to the United States. To do this, I estimate a discrete choice dynamic programming model where a person's decisions depend on the location of their spouse. I use a new identification strategy to estimate the effect of border enforcement on immigration, accounting for the variation in the allocation of resources along the border. I estimate the model using data on individual immigration decisions from the Mexican Migration Project. Counterfactuals show that a 10% increase in Mexican wages would decrease the number of years spent in the U.S. by about 8%. A 50% increase in enforcement reduces immigration by up to 11.6%.

JEL Codes: F22, J61

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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. A much higher fraction of immigrants from Mexico move to the U.S. illegally than immigrants from other countries.[1] These large migration rates affect the economies of both countries. For example, migrants send remittances back home, which support development in Mexico.[2] 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). Supporters of NAFTA argued that the treaty would increase Mexican wages and consequently reduce illegal immigration.

In this paper, I study how wage differentials and U.S. border enforcement affect an individual's immigration decisions. I analyze these questions in a dynamic setting, which is important because the data shows that repeat and return migration are common. In addition, I allow for a person's location choices to depend on where their spouse is living. This is the first paper on this topic that allows for an interaction between the decisions of spouses in a dynamic setting. To evaluate the effectiveness of border enforcement, I use a new identification strategy, which accounts for the variation in the allocation of enforcement resources along the boder.

Most of the migration literature uses a static framework; however, the trends in the data imply that a dynamic setting is more appropriate. Kennan and Walker (2011) develop a dynamic model where individuals move within the U.S. based on income differences across locations. I modify their framework to account for the differences caused by illegal immigration. Hong (2010) applies a similar framework to Mexico-U.S. immigration, focusing on the legalization process. Thom (2010) develops and estimates a model of circular migration for Mexican immigrants, incorporating savings decisions. These papers study only male migration, whereas my model allows for interactions between the decisions of married couples. The data shows that this is important, in that 5.7% of women with a husband in the U.S. move each year, compared to on overall female migration rate of 0.6%.[3] Gemici (2011) estimates a dynamic model of migration decisions with intra-household bargaining, using U.S. data. In her model, married couples make a joint

[1] Around 56% of the Mexicans moving to the U.S. do so illegally, compared to 17% of immigrants from other countries (Hanson, 2006).

[2] In 2004, remittances comprised 2.2% of Mexico's GDP, contributing more foreign exchange to Mexico than tourism or foreign direct investment (Hanson, 2006).

[3] Cerrutti and Massey (2001) find that women usually moving to the U.S. following a family member, whereas men are much more likely to move on their own. Massey and Espinosa (1997) find that illegal immigrants are more likely to return to Mexico if they are married.

decision on where to live, whereas the data from Mexico shows that couples often live in different locations.

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.[4] Border enforcement, measured as the number of man-hours spent patrolling the border, affects the moving cost only for illegal immigrants. U.S. enforcement varies along different regions of the border. In the model, individuals who move to the U.S. illegally also choose where to cross the border. The data shows that as enforcement at the main crossing point increased, migrants shifted their behavior and crossed at alternate points.[5] 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 addition, in the model, individual's choices depend on the location of their spouse. 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.

I estimate the model using data on individual immigration decisions from the Mexican Migration Project (MMP). 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. A 10% increase in Mexican wages reduces the average number of years that a person lives in the U.S. by about 8%.

Recently, there has been a lot of debate in the U.S. about increasing border enforcement. I show that increased border enforcement would reduce both the number of people that immigrate and the number of moves per migrant. 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. 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. over a lifetime by approximately 5%. 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 close to 12%. This suggests that the effect of increased enforcement depends on the allocation of the new resources.

Recent policy proposals in the U.S. suggest focusing efforts on identifying and de-

[4](Kossoudji and Cobb-Clark, 2000) find that illegal immigrants receive lower wages than legal immigrants and are less likely to work in high skill occupations when in the U.S.

[5]Gathmann (2008) studies the behavior of repeat migrants and finds that they switch their crossing point in response to an increase in enforcement at the initial crossing point.

porting illegal immigrants.[6] This would reduce immigration by forcing people to return to Mexico. It would also lower the value of living in the U.S., which would deter illegal immigration. I assume that people believe that there is a 10% chance that they would be deported if living in the U.S. illegally. The deterrence effect of this policy decreases immigration by around 30%.

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 section 5 provides descriptive statistics. The estimation is explained in Section 6, and the results are in Section 7. The counterfactuals are in Section 8, and Section 9 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 an increase in U.S. wages relative to Mexican wages positively affects apprehensions at the border, implying that more people attempted 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 research uses 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. Hanson and Spilimbergo (1999) find that increased enforcement led 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.

Changes in enforcement can affect not only initial but also return migration decisions. Angelucci (2005), using the MMP data, finds that border enforcement affects initial and

[6] The Support our Law Enforcement and Safe Neighborhood Act was passed in Arizona in April 2010. This law increased efforts to identify and deport illegal immigrants living in Arizona. Most of the law's strictest measures were blocked by a federal court, and it is currently being debated in the Supreme Court. Nonetheless, this has been a discussed policy option.

return migration rates. Her framework permits analysis of initial and return migration decisions separately using a reduced form framework. By estimating a structural model, I can perform counterfactual analyses to calculate the net effect of changes in enforcement on illegal immigration.

## 3. Model

At each point in time, each person chooses a location from a set of choices in Mexico and in the U.S. If he moves, he pays a moving cost, where I allow for unobserved heterogeneity in the moving costs. Decisions depend on whether an individual is able to move to the U.S. legally. Legal status affects the wage distribution in the U.S. and the cost of moving to the U.S.[7] I assume that once an illegal immigrant enters the U.S., there is no chance that he will be deported.[8]

I assume a finite horizon, meaning that the model can be solved using backwards induction. At the start of each period, each person 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. I assume that these follow an extreme value type I distribution, and solve the model following McFadden (1973) and Rust (1987).

Decisions depend on a person's marital status. For married couples, utility depends on whether a person is living at the same country as his spouse. Since individual's decisions are related, this is a game between the husband and wife. I solve for a Markov perfect equilibrium (Maskin and Tirole, 1988). I make some assumptions on the timing of decisions to ensure that there is only one equilibrium. For each household, I define a primary and a secondary mover. The primary mover picks a location first, so he does not know his spouse's location in that period when he makes this choice. 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. [9]

[7] I assume that all people who choose to move to the U.S. are successful. Passel, Bean, and Edmonston (1990), Kossoudji (1992), Donato, Durand, and Massey (1992), Blejer, Johnson, and Porzecanski (1978), and Crane, Asch, Heilbrunn, and Cullinane (1990) find that migrants who are caught at the border attempt to enter the U.S. again. Increased enforcement raises the monetary costs of moving by increasing the cost of hiring a smuggler (Gathmann, 2008) or by increasing the expected number of attemps before successfully crossing.

[8] Espenshade (1994) finds that only 1-2% of illegal immigrants living in the U.S. are caught and deported in each year.

[9] An alternative approach would be to model the household problem, where the household jointly decides where the husband and wife will live in each period. However, this is computationally difficult, as

## 3.1 Model Setup

I denote marital status with a superscript $m$, where $m = 1$ is the primary mover, $m = 2$ is a secondary mover, and $m = 3$ is a single period. I denote a person's spouse with the superscript $s$.

**State Variables** At the start of each period, a person learns whether he can move legally at that time.[10] I assume that once a person is able to immigrate legally, this option remains with him forever. 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.

State variables include a person's location in the previous period ($\ell_{t-1}$) and their characteristics $X_t$ . When the secondary mover picks a location, the primary mover has already chosen where to live in that period, so the location of the spouse ($\ell_t^s$) is known and is part of the state space. For the primary mover, the location of the spouse in the previous period ($\ell_{t-1}^s$) is part of the state space. The characteristics and legal status of one's spouse ($X_t^s$ and $z_t^s$) are part of the state space. To simplify notation, denote $\Delta_t$ as the characteristics and legal status of an individual and their spouse, so $\Delta_t = \{X_t, z_t, X_t^s, z_t^s\}$. The value function also depends on person's wages 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 $w(X_t, z_t, j)$.

**Choice Set** 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. Denote the choice set for primary movers as $J^1(\ell_{t-1}^1, z_t^1)$, where

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

The location choices for single people are the same as for primary movers, so $J^3(\ell_{t-1}, z_t) = J^1(\ell_{t-1}, z_t)$.

I assume that secondary movers can only live in the U.S. if the primary mover is living there.[11] Then the choice set can be limited, depending on the location of the primary

the state space would have to contain the location of the husband and wife. Furthermore, the sequential nature of decisions in the data show that it is logical to model this as a sequence of individual decisions. In the data, 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.

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

[11] Cerrutti and Massey (2001) and Massey and Espinosa (1997) find that married women very infrequently

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

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

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.

**Payoff shocks** I denote the set of payoff shocks at time $t$ as $\eta_t = \{\eta_{jt}\}$, where $j$ indexes locations.

**Utility** The utility flow depends on a person's location $j$, characteristics, legal status, and spouse's location, and it is written as $u(j, X_t, z_t, \ell_t^s)$. Utility depends on whether or not a person is at their home location, which is included in their characteristics $X_t$. Utility also depends on whether or not a person is at the same location as their spouse.

**Moving costs** The moving cost depends on which locations a person is moving between, their characteristics, and their legal status. I denote the cost of moving from location $\ell_{t-1}$ to location $j$ as $c_t(\ell_{t-1}, j, X_t, z_t)$. The moving cost is normalized to zero if staying at the same location.

**Transition probabilities** There are two unknown states: future legal status and spouse's location. For the primary mover, he is uncertain of his spouse's location in the current period. The secondary mover will be unsure of her spouse's location in the next period. For the primary mover, denote the probability of being in the state with legal status $z_{t+1}$ and having a spouse in location $\ell_t^s$ in this period as $\rho_t^1(z_{t+1}, \ell_t^s | j, \Delta_t, \ell_{t-1}^s)$. For the secondary mover, the transition probability is written as $\rho_t^2(z_{t+1}, \ell_{t+1}^s | j, \Delta_t, \ell_t^s)$

## 3.2 Value Function

In this section, I derive the value functions 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

move to the U.S. when their husband is not there.

that there is no spouse's location in the state space.[12] 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.

### 3.2.1 Secondary Movers

The value function for secondary movers is defined as follows:

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

The value of living in each location has a deterministic and a random component ($v_t^2(\cdot)$ and $\eta_t$, 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 flow payoff of living in location $j$, denoted at $\tilde{v}_t(\cdot)$, is defined as

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

Then, the deterministic component of living in a location is the flow payoff plus the discounted expected value of living there in the next period:

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

For a given legal status and location of primary mover, the expected future value is given by

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

In equation (2), $\gamma$ is Euler's constant ($\gamma \approx 0.58$). The unconditional expected value is given by

[12] I do not allow for expectations over transitions between being single and married. Therefore, a person who is single expects to remain single forever. The data shows some correlation between migration decisions and marital status. Moving to the U.S. does not seem to affect marital status, but people who have recently returned to Mexico are more likely to get married. The model does not account for these transitions.

$$EV^2_{t+1}(j, \Delta_{t+1}, \ell^s_{t+1}, \eta_{t+1}) =$$
$$\sum_{z_{t+1}, \ell^s_{t+1}} \rho^2_t(z_{t+1}, \ell^s_{t+1} | j, \Delta_t, \ell^s_t) \times E\left[V^2_{t+1}(j, \Delta_{t+1}, \ell^s_{t+1}, \eta_{t+1}) | z_{t+1}, \ell^s_{t+1}\right] ,$$

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 used to develop the likelihood function in Section 6.5. In addition, it is used to calculate the transition probabilities for the primary mover, who is concerned with the probability that his spouse makes a given decision.

Since I assume that the payoff shocks are distributed with an extreme value distribution, the choice probabilities take a logit form. The probability that a person picks location $j$ is given by the following formula:

$$P^2_t(j | \ell_{t-1}, \Delta_t, \ell^s_t) = \frac{\exp\left(v^2_t(j, \ell_{t-1}, \Delta_t, \ell^s_t)\right)}{\sum_{k \in J^2(\ell_{t-1}, z_t, \ell^s_t)} \exp\left(v^2_t(k, \ell_{t-1}, \Delta_t, \ell^s_t)\right)} \tag{3}$$

### 3.2.2 Primary Movers

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

$$\tilde{v}_t(j, \ell_{t-1}, X_t, z_t, \ell^s_t) = u(j, X_t, z_t, \ell^s_t) - c(\ell_{t-1}, j, X_t, z_t)$$

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:

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

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.

I define the value function for the primary mover as follows:

$$V^1_t(\ell_{t-1}, \Delta_t, \ell^s_{t-1}, \eta_t) = \max_{j \in J^1(\ell_{t-1}, z_t)} v^1_t(j, \ell_{t-1}, \Delta_t, \ell^s_{t-1}) + \eta_{jt} \tag{5}$$

The function $v_t^1(\cdot)$ is defined as

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

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:

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

The unconditional expected value is

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

The transition probabilities are explained in more detail in Section 3.2.3.

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

$$P_t^1(j|\ell_{t-1}, \Delta_t, \ell_{t-1}^s) = \frac{\exp\left(v_t^1(j, \ell_{t-1}, \Delta_t, \ell_{t-1}^s)\right)}{\sum_{k \in J^1(\ell_{t-1}, z_t)} \exp\left(v_t^1(k, \ell_{t-1}, \Delta_t, \ell_{t-1}^s)\right)} \tag{6}$$

### 3.2.3 Transition Probabilities

The transition probabilities are over future legal status and a spouse's future decisions. 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. I assume that the probability that a person can move to the U.S. legally depends on his characteristics $X_t$ and location $\ell_t$. This allows the transition rates between legal status to vary based on whether or not a person is living in the U.S. Denote the probability that a person remains an illegal immigrant at time $t+1$ as $\delta(X_t, \ell_t)$.

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

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

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

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 $Z(z_t)$ 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.

Denote the matrices $\Lambda_t^1$ and $\Lambda_t^2$ as the transition probabilities for primary and secondary movers, respectively, where

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

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

The matrices $\Lambda_t^1$ and $\Lambda_t^2$ give the probability that a person has a given legal status and has a spouse living in a certain location. In each matrix, 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. Then

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

For primary movers, there is uncertainty over where the secondary mover will live in the current 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 mover's 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

I estimate the model using data from the Mexican Migration Project (MMP), a joint project of Princeton University and the University of Guadalajara.[13] The MMP is a repeated cross-sectional dataset that started in 1982, with the last currently available round from 2009.

For household heads and spouses, the MMP collects a lifetime migration history, which I use 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.

The MMP makes several efforts to capture the current as well as the past migrant population. If a household reports that a family member currently lives in the U.S., the MMP researchers ask for information about that person. However, households who have entirely moved to the U.S. would be missing from the sample. Interviewers also attempt to survey individuals from each community who are currently living in the United States, although this sample is small, meaning that the MMP most likely undersamples the current migrant population. This implies that my results place a greater weight on the decisions of temporary migrants.

In addition, the MMP sample is not representative of Mexico, as the surveyed communities are mostly those in rural areas with high migration propensities. Western-central Mexico, the region with the highest migration rates historically, is over-sampled.[14] Therefore, the results of this paper apply to this specific section of the Mexican population.

One question in this paper is how changes in 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 10,295, in which I observe each person's location from age 17 until the year surveyed.[15]

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

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

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

The MMP has wage data when people are in the U.S., which I use to compute the wage distribution for Mexican migrants illegally living in the United States. This is another strength of the MMP data, in that I cannot construct a wage distribution for illegal immigrants with other datasets, which often report country of birth but not legal status. For the wages of legal immigrants, I use CPS data.[16] 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.[17] CBP divides the U.S.-Mexico border into 9 regions, and the data reports the man-hours spent patrolling each sector.

# 5. 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. Those who move to the U.S. are mostly male. I also show the education levels of each group. Each row shows the percent of a group (i.e. internal movers) with a given level of education. People who move to the U.S. have the least education. 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. 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 close to 5% of the sample.

## 5.1 Immigration Decisions

Between 1980 and 2004, an average of 2.3% of the people in the sample living in Mexico moved to the U.S. in each year. This varies significantly with legal status, as the average migration rate for people who can move legally is around 30%.

Using a probit regression, I estimate the probability that a person who lives in Mexico

[16] I could also use CPS data for illegal immigrants, but I expect that the CPS data oversamples legal immigrants relative to illegal immigrants.

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

moves to the U.S. in a given year. The coefficient estimates are reported in the first column of Table 2. As education increases above 11 years, the probability of moving to the U.S. decreases. The effect of age on migration 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. This regression shows that a person whose spouse is living in the U.S. is more likely to immigrate, showing that it is important to control for spouse's decisions in the model.

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 2. 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.

One of the motivations for the dynamic model estimated in this paper is that repeat migration is common. In the sample, the average number of moves to the U.S. per migrant is 1.4, showing that many migrants move more than once.[18] Men move an average of 1.5 times, whereas women move 1.1 times. Women move less and are less likely to return migrate, implying that when women move it is more of a permanent decision.

Table 3 shows the average duration of stays in the U.S., splitting the sample by education, legal status, and gender. Legal immigrants stay in the U.S. for longer periods of time, and women stay for longer than men. Durations increase with education for illegal immigrants and for men. There is no clear trend with education for legal immigrants or for women. These observations are censored, however, as we do not know the full duration of stays for people who are surveyed while living in the U.S. This suggests that the average durations are higher than those reported in the Table 3.

## 5.2 Internal Migration

In the model, individuals choose from a set of locations in Mexico and the United States. Internal migration is fairly common, as close to 20% 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.

[18] When I use all of the MMP data, this number is 2.5, which is significantly higher. This is because the estimation sample is quite young, since I only use people who are 17 or younger in 1980, so I am dropping the older respondents who were likely to have moved more times.

To study the determinants of location choices, I take three of the states with the most internal migrants in the MMP data (Guanajuato, Jalisco, and Michoacań) 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, 43%, 63%, and 62% of migrants moved to bordering states, respectively. In all of these states, most remaining moves are to either high wage locations or to Mexico City.[19]

## 5.3 Border Enforcement

To measure border enforcement, I use data from 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.[20] Figure 1 shows the number of man-hours spent patrolling each region of the border over time.[21] 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 and the Rio Grande Valley, although the growth started later than at San Diego. 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 1 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.[22] Figure 2 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 63% of illegal immigrants crossed the border at San Diego.

[19] These trends follow what is normally found in the internal migration literature. For example, see Greenwood (1997).

[20] 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.

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

[22] 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 .

This decreased to 31% post-1995. 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.[23]

# 6. Estimation

I estimate the model using maximum likelihood. I assume that a person has 27 location choices, – 23 in Mexico and 4 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.[24] The locations in the U.S. are 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 where to cross the border. The U.S. government divides the border into 9 regions. However, very few people in the data cross at some of these points, making identification of the fixed cost of crossing difficult. I reduce the number of crossing points to 7 to avoid this problem.[25] Therefore, an illegal immigrant has 28 choices in the U.S.- the four locations combined with seven 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.[26]

## 6.1 Wages

Table 4 shows the average hourly wages in the U.S. (for legal and illegal immigrants) and in Mexico (in 2000 dollars), splitting the sample by education. There are large wage differentials between the 2 countries, which decrease with education. Legal immigrants earn more than illegal immigrants and also realize stronger returns to education.

I regress wages on education, gender, age, and whether or not a person has family

[23]One concern could be that the border patrol hours are not adequately controlling for the levels of enforcement, as there are other mechanisms that the U.S. government uses to monitor the border. Technology such as stadium lighting, infra-red cameras, and ground sensors are used to aid border patrol agents. However, border patrol hours are highly correlated with total expenditures on border patrol.

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

[25]Del Rio was combined with Marfa and Yuma was combined with El Centro.

[26]To estimate the model, I assume that people do not expect changes in wages and border enforcement over time.

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. [27]

The results of this regression for illegal immigrants living in the U.S. are shown in the first column of Table 5. Wages increase with education. 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 between ages 17 and 65. Typically, older people have more experience and therefore earn higher wages. However, many illegal immigrants work in agriculture or construction, occupations which require physical labor and therefore may place a premium on youth. In the data, 31% of the jobs are in agriculture, 42% are in manufacturing and construction, and 21% are in services.[28]

The second column of Table 5 show the results of the wage regression for legal immigrants living in the U.S. Returns to education and age are stronger than for illegal immigrants, as expected.

The third column of Table 5 shows 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. There are fewer educated people in Mexico than in the U.S., leading to strong returns to skills.

I use the results of these regressions to calculate an expected wage for each person in each location and year. I assume that there is no wage variation, so each person is earning his expected wage in his current location.[29]

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. 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.[30] However, this is done in a static framework, and would be much more difficult to implement in a model with dynamics. In addition, the data on wage realizations in the U.S. for Mexican immigrants is limited, again making it hard to address the selection issue.

[27] This variable is only available for illegal immigrants, because it is not in the CPS data.

[28] 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.

[29] A person's income draw when in the U.S. could affect whether or not he stays. However, the retrospective data does not include wages at each point in time, so I do not have the data to include this in the estimation.

[30] 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.

## 6.2 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.

Networks, defined as the people that an individual knows who are already living in the U.S., can affect the cost of moving to the United States. [31] 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.[32] 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.[33]

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.

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.

Recall from Section 3.2 that $c_t(\cdot)$ is the moving cost function. This function depends on a person's legal status and on which 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 $\ell_2$ includes both a location in the U.S. and a border

[31] Colussi (2006), Massey and Espinosa (1997), and Curran and Rivero-Fuentes (2003) find evidence that networks affect immigration decisions.

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

[33] 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.

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:

$$
\begin{aligned}
c_t^1(\ell_1, \ell_2, X_t) &= \lambda_1 + \lambda_2 d(\ell_1, \ell_2) + \lambda_3 rr(\ell_1) + \lambda_4 age + \lambda_5 pop(\ell_2) \\
&+ \sum_{q=1}^{N_e} \lambda_q^e educ_q \\
c_t^2(\ell_1, \ell_2, X_t) &= \lambda_1 + \lambda_2 d(\ell_1, \ell_2) + \lambda_3 rr(\ell_1) + \lambda_4 age + \lambda_5 pop(\ell_2) \\
&+ \sum_{q=1}^{N_e} \lambda_q^e educ_k + \lambda_6 + \lambda_7 b_{kt} + \lambda_k^b \\
c_t^3(\ell_1, \ell_2, X_t) &= \lambda_8 + \lambda_9 d(\ell_1, \ell_2) + \lambda_{10} age + \lambda_{11} pop(\ell_2) \\
c_t^4(\ell_1, \ell_2, X_t) &= \lambda_{12} + \lambda_{13} d(\ell_1, \ell_2) + \lambda_{14} age + \lambda_{15} pop(\ell_2)
\end{aligned}
$$

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. ($\lambda_1$), back to Mexico ($\lambda_8$), or within Mexico ($\lambda_{12}$). If moving to the U.S. illegally, I allow for an increase in the fixed cost ($\lambda_6$). If moving to the U.S., the distance from a location to the railroad (denoted as $rr(\ell_1)$) affects the moving cost. The term $b_{kt}$ is the level of border enforcement at crossing point $k$ at time $t$, and $\lambda_7$ is the effect of border enforcement on the moving cost. Each border crossing point has its own fixed cost, denoted as $\lambda_k^b$.[34] 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.

The cost of moving also depends on age, which affects moving costs linearly. The population size of the destination also affects moving costs.[35] This allows the model to account for the empirical fact that people are more likely to move to larger locations. 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 $\lambda_q^e$ is the estimated fixed cost for education group $q$. The term $educ_q$ is a dummy variable that equals 1 if a person is in education group $q$.[36]

[34] There are 7 crossing points, and I estimate 6 fixed costs. The 7th is set to 0 and the other fixed costs represent the change in fixed cost between that point and the baseline crossing point.

[35] An alternative specification is to scale the number of payoff shocks according to the population size at the destination.

[36] In the estimation, I set this to 0 for people with 0-4 years of education. Then the other parameters give the change in costs compared to people with 0-4 years of education.

## 6.3 Transitions over 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.

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. Official U.S. policy states that people who are currently residing in the U.S. after moving illegally should not be granted visas. However, these results show that this policy is not enforced in practice. I use the results of this regression to impute a probability that each person is granted legal status. 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.

## 6.4 Utility Function

The utility function depends on a person's wage, whether or not he is living at his home location, and whether or not a family member is in the U.S. (as another measure of network effects). For married couples, utility depends on whether a person is at the same country as his spouse. I write the utility function as

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

Utility depends on a person's wage, location $\ell_t$, spouse's location $\ell_t^s$ (if married), and characteristics $X_t$, which affect utility through the home location $H$ and through the fam-

ily dummy variable $f$. I assume that utility is linear in a person's wage, where $\alpha_w$ 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 $\alpha_H$ 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 $\alpha_S$ if he is not in the same country as his spouse. People with family in the U.S. get an increase in utility equal to $\alpha_F$ when living there.

## 6.5 Likelihood Function

I estimate the model using maximum likelihood. I assume that there is unobserved heterogeneity over moving costs. In particular, I assume that there are two types of individuals, where one group has infinitely high moving costs and will never move to the U.S.

Denote the set of parameters to be estimated as $\theta_\tau$ for a person of type $\tau$, where $\theta_\tau$ includes the utility and moving cost parameters. For each individual, I observe a history of location choices $\mathbb{L} = \{\ell_0, \ell_1, ..., \ell_T\}$. 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 the probability of seeing an observed history for household $i$ as $\chi(\mathbb{L}_i^1, \mathbb{L}_i^2, \theta_\tau)$, where $\mathbb{L}_i^1$ and $\mathbb{L}_i^2$ are the location histories of the primary and secondary mover, respectively. Then

$$\begin{aligned}
\chi(\mathbb{L}_i^1, \mathbb{L}_i^2, \theta_\tau) &= P_1^1(\ell_{i1}^1 | \ell_{i0}^1, \Delta_{i1}^1, \ell_{i0}^2, \theta_\tau) \times P_1^2(\ell_{i1}^2 | \ell_{i0}^2, \Delta_{i1}^2, \ell_{i1}^1, \theta_\tau) \\
&\times P_2^1(\ell_{i2}^1 | \ell_{i1}^1, \Delta_{i2}^1, \ell_{i1}^2, \theta_\tau) \times P_2^2(\ell_{i1}^2 | \ell_{i1}^2, \Delta_{i2}^2, \ell_{i2}^1, \theta_\tau) \\
&\times ... \\
&\times P_T^1(\ell_{iT}^1 | \ell_{i,T-1}^1, \Delta_{iT}^1, \ell_{i,T-1}^2, \theta_\tau) \times P_T^2(\ell_{iT}^2 | \ell_{i,T-1}^2, \Delta_{iT}^2, \ell_{iT}^1, \theta_\tau)
\end{aligned}$$

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. In addition, the choices of one's spouse enter into an individual's state space. Since the types are unobserved, for each household I can calculate the probability that I see a given history, multiplied times the probability that a household has type $\tau$. Denote $p_\tau$ as the probability that a household has type $\tau$.[37]

[37] I assume that any person who can move to the US legally is a mover type.

The log-likelihood function is the sum, over households, of the log of the probability of seeing each history:

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

# 7. Results

Table 7 reports the utility parameter estimates, which 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.[38] In addition, people with family in the U.S. have higher utility when living in the U.S. than those who do not. There are mover and stayer types in the model; the estimation is set so that the fixed cost of moving to the U.S. is infinity for stayer types so they will never choose to make that move. I find that the probability that a household is a mover-type is about one-half.

Table 8 shows the moving cost parameters (excluding the parts related to illegal immigration). There are three moving cost functions: Mexico to U.S. migration, return migration, and internal migration. The first component of the moving cost is the fixed cost of moving, which is negative when returning to Mexico. This is because people earn lower wages when they return to Mexico, and a negative fixed cost is necessary to match the observed high return migration rates. This implies that there is, as expected, some non-financial benefit to living in Mexico, as compared to living in the U.S. I allow the fixed cost to vary by gender, and find that this does not substantially affect the results. The moving cost also depends on the distance between locations. For Mexico to U.S. migration and internal migration, the cost increases in distance, as expected. For illegal immigrants, the distance is the distance from the Mexican state to the crossing point plus the distance from the crossing point to the U.S. destination. This implies that the location choices and crossing point decisions will be related. For return migration, the moving cost decreases with distance. The location in Illinois has the highest return migration rates, and is the furthest from the border.[39] This behavior is driving this parameter estimate. I also allow for age to affect the moving cost. When moving to the U.S. or moving within Mexico, moving costs increase with age, which implies that standard human capital theory does

[38] I estimated a simpler version of this model, taking away the utility preference for living at the same location as a person's spouse. This leads to a significant change in the likelihood at the optimal point, where equality of the likelihood with the original and simpler model was rejected by a likelihood ratio test.

[39] This could be explained by climate, in that the weather in Illinois is much colder than Texas or California.

not fully explain why younger people are more likely to immigrate. Other factors outside the model make younger people more likely to move. For return migration, older people are more likely to move. As people become older, they have more of an incentive to return to their home country. Moving costs also depend on population size, in that we would expect people to be more likely to move to larger locations.[40] For return migration and internal migration, the moving cost decreases with population size, predicting that people are more likely to move to larger locations. For Mexico to U.S. migration, the effect is positive but small. Networks affect moving costs through the distance to the railroad. The railroad factor moves in the expected direction, in that larger networks decrease moving costs. When moving to the U.S., I allow moving costs to be affected by education using dummy variables, where the excluded group is those with 0-4 years of education.

Table 9 shows the parameter estimates relating to illegal immigration. The fixed cost of moving is higher 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. For example, San Diego is where the greatest share of people cross, but it also has the highest enforcement. Therefore the estimation finds that this point has the lowest fixed costs.

Table 10 shows the model fit. I calculate 3 statistics in the data: the percent of the sample that moves to the U.S., the number of moves to the U.S. per migrant, and the average duration of each move to the U.S. I then simulated the model and calculated the model's predicted values for each of these variables. Overall, the model fits the data fairly well.

To understand how different factors affect illegal immigration rates in the model, I calculate migration probabilities for individuals with different characteristics. Table 11 shows the probability that a 30 year old primary mover who is living in Guanajuato moves to the U.S. in 2004. I vary his education level and whether or not he has family in the U.S. People with the most education are the least likely to migrate. This is because the wage differentials decrease with education, giving the most educated people the smallest incentive to move. Family networks increase the likelihood of migration.

In Table 12, I calculate return migration rates for a 30 year old primary mover who is living in California.[41] I vary education levels, where his spouse is living, and family networks. If his spouse is living in Mexico, then has more of an incentive to return to his home location, due to the utility gain from living in the same location as his spouse. If

[40] An alternative way to control for this is to scale the number of payoff shocks by the population size at the destination.

[41] To make this calculation, I had to fix the home location, which was set as Guanajuato.

his spouse is in the U.S., he has less of an incentive to return migrate. Table 12 shows that this leads to substantial differences in return migration rates. Because utility in the U.S. is higher for people with family networks, return migration rates are lower for people who have family in the U.S.

# 8. Counterfactuals

I use counterfactuals to understand how changes in relative wages and U.S. policy affect immigration decisions. In each case, I first calculate how the change would affect initial migration and return migration rates. I then simulate how behavior would change over a lifetime to calculate the net effect. The first counterfactual raises Mexican wages by 10%, holding U.S. wages constant. The second estimates the effect of a 50% increase in U.S. enforcement. In the last two counterfactuals, I estimate the effects of different types of U.S. policies. I look at the effects of a policy which eliminates legal migration to the U.S. I also show the effect of a policy where people living in the U.S. illegally believe that they could be deported.

## 8.1 Increased Mexican Wages

In the first counterfactual, I look at the effects of a 10% increase in Mexican wages, holding U.S. wages constant. Table 13 shows migration and return migration rates for a 30 year-old primary mover with 5-8 years of education, whose home location is Guanajuato, and who has a family member living in the U.S. I show Mexico to U.S. immigration rates when he is living in Guanajuato. I also calculate return migration rates when living in California, assuming that his spouse lives in Mexico. The first row shows the migration rates in the baseline case. The second row shows the migration rates after wages in each Mexican state increase by 10%. This increases the value of living in Mexico, thereby reducing migration rates and increasing return migration rates.

I then use simulations to see how this affects immigration behavior over a lifetime. I calculate 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 spent living in the U.S. per move, and the average number of years a person lives in the U.S. over a lifetime. The first row of Table 14 shows the baseline simulation. The second row shows the results from a 10% increase in Mexican wages. After this change, 4.5% 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 about 3%. This follows the results in Table 13, 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 around 8%.

## 8.2 Increased Border Enforcement

Next, I calculate how increased enforcement affects immigration, assuming that the man-hours allocated to enforcement at each crossing point increases by 50%. In the third row of Table 13, I show the effects on annual migration rates. People are less likely to move, and current migrants are also less likely to return migrate, with the latter effect occuring because current migrants know that it will be harder to enter the U.S. in the future. This implies that the overall effect of increased enforcement is ambiguous, as fewer people move, but those that move stay in the U.S. for longer.

The third row of Table 14 shows the results of increased enforcement over a lifetime, which allows us to see the overall effect of this policy change. The percent of the sample that moves decreases, the number of moves per migrant decreases, and duration of each move increases. Overall, this increase in enforcement reduces the average amount of time a person lives in the U.S. by about 4.7%.

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, where the extra resources are allocated to minimize illegal immigration rates, assuming that this is the government's objective. The solution to the static problem in my model 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 a 50% increase in enforcement. To get closest to this point, the extra resources should be allocated to the sectors of the border with the lowest fixed costs of crossing. These 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 fourth row of Table 13 shows the effects of this policy on annual migration rates. The qualitative changes are the same as with the uniform increase in enforcement, but the magnitudes are substantially larger. The fourth row of Table 14 shows the overall effects of this policy change. As with the uniform increase in enforcement, fewer people move, and the duration of each move increases. When the extra enforcement is allocated following this equal costs strategy, the average number of years spent in the U.S. decreases by 13.2%, whereas it decreased by around 5% with the uniform increase in enforcement. This shows that the effect of increased enforcement depends on on the allocation of the extra resources.

Its interesting to compare the effects of increased enforcement to increased Mexican wages. The 50% increase in enforcement, allocated following the equal costs strategy, de-

creases immigration by about 13%. I compare that to the approximate increase in Mexican wages required to reach the same goal. This would occur with approximately a 15% increase in Mexican wages, which is a relatively small narrowing of the Mexico-U.S. wage gap. In comparison, a 50% increase in border enforcement is an expensive policy. Expenditures on border enforcement were estimated to equal $2.2 billion in 2002, meaning that this policy could cost over $1 billion (Hanson, 2005).

## 8.3 Ending Legal Immigration

In the model, individuals believe that they have some chance of becoming legal immigrants in future periods. In the next set of counterfactuals, I take away this possibility. 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 would increase. Second, wages are higher for legal immigrants. If there is no chance of becoming a legal immigrant in the future, then the value of living in the U.S. decreases, lowering immigration rates. The fifth row of Table 13 shows the effects of this policy on annual migration rates. Immigration rates decrease and return migration rates increase, indicating that the wage effect dominates. In the estimation, the probability of becoming a legal immigrant is much higher when already living in the U.S., which strengthens the wage effect and drives these results. In the fifth row of Table 14, I show the effects of this policy over a lifetime. Fewer people move, and the duration of each trip to the U.S. decreases. These effects combine to decrease the amount of time that a person lives in the U.S. by about 12%.

## 8.4 Deportation Policies

I analyze the deterrence effects of a policy where the U.S. government increases efforts to identify and deport illegal immigrants. Such a policy would have two effects on immigration. First, it would directly reduce immigration by forcing individuals to return to Mexico. It would also have a deterrence effect, as if people know that there is some exogenous probability that they will be deported, the value of living in the U.S. is lower. In this simulation I focus only on the deterrence effect, assuming that people believe that there is a 10% chance they will be deported if living in the U.S. illegally. [42]

[42] In the initial model, following U.S. policy, there was no chance of being deported.

This policy lowers the expected value of living in the U.S., decreasing immigration rates and increasing return migration. The last row of Table 13 shows how this policy affects annual migration rates. As expected, it decreases Mexico to U.S. migration rates and increases return migration rates. The last row of Table 14 shows the overall effect of the deportation policy. Both the number of people that move and the duration of each move decrease, combining to lower the years in the U.S. per person by around 30%.

# 9. 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 allow for a person's decisions to depend on the location of their spouse. I model decisions in a two-step process, where individuals in a household make decisions sequentially. I use this model to understand how wage differentials and U.S. border enforcement affect an individual's immigration decisions.

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.

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 around 8%. 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 re-enter 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. by approximately 5%. 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 about 12%. This shows that the effects of enforcement are 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. Hanson (2005) reports that expenditures on border enforcement equalled approximately $2.2 billion in 2002. Therefore, I find that

about an extra $1 billion in expenditures would increase immigration by 12%. Furthermore, I find that the effects of increased enforcement strongly 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.

This paper studies immigration in a partial equilibrium framework, not allowing for general equilibrium effects. Increases in immigration could drive down wages in the U.S. or cause higher wages in Mexico. However, there is no clear conclusion with regard to these general equilibrium effects. Kennan (2012) develops a model that predicts that migration will change wage levels but not the wage ratios between countries. The empirical evidence is mixed, as some research finds a little effect of immigration on U.S. wages while other authors have found larger effects.[43] Nonetheless, this is an important question that could be addressed in future work. This paper is a first step in that direction and helps to provide the foundation for such an analysis.

[43] LaLonde and Topel (1997), Smith and Edmonston (1997), and Borjas (1999) find a weak correlation between immigration inflows and wage changes for low skilled U.S. workers. Borjas, Freeman, and Katz (1997) find larger effects.

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# Tables and Figures

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 | 47.8% | 79.3% | 85.5% | 35.8% | 76.2% |
| Percent that is Married | 83.6% | 83.5% | 74.7% | 89.9% | 72.0% |
| Average Age | 27.7 | 20.0 | 25.2 | 26.0 | 32.6 |
| 0-4 Years Education | 11.8% | 15.1% | 9.6% | 13.9% | 8.9% |
| 5-8 Years Education | 33.4% | 39.3% | 40.1% | 34.1% | 42.3% |
| 9-11 Years Education | 29.5% | 31.3% | 33.7% | 30.9% | 26.1% |
| 12 Years Education | 14.4% | 10.7% | 8.9% | 13.3% | 15.3% |
| 13+ Years Education | 10.9% | 3.6% | 7.8% | 7.9% | 7.3% |
| Number of Observations | 1,470 | 1,404 | 282 | 6,676 | 463 |

Table 2: Probability of Moving

| | Moves to U.S. | Return Migrates |
|---|---|---|
| 5-8 Years Education | 0.03 | 0.08 |
| | (0.03) | (0.05) |
| 9-11 Years Education | -0.03 | -0.04 |
| | (0.03) | (0.05) |
| 12 Years Education | -0.13*** | 0.008 |
| | (0.04) | (0.07) |
| 13+ Years Education | -0.36*** | -0.04 |
| | (0.05) | (0.08) |
| Age | -0.09*** | -0.08** |
| | (0.02) | (0.03) |
| Age-squared | 0.001*** | 0.001** |
| | (0.0003) | (0.0006) |
| Family in U.S. | 0.28*** | -0.13*** |
| | (0.02) | (0.03) |
| Male | 0.93*** | -0.11** |
| | (0.03) | (0.05) |
| Legal | 1.12*** | -0.98*** |
| | (0.03) | (0.04) |
| Married | 0.12*** | -0.92*** |
| | (0.02) | (0.07) |
| Spouse in U.S. | 1.13*** | - |
| | (0.04) | |
| Spouse in Mexico | - | 1.63*** |
| | | (0.07) |
| Moved to U.S. Before | 0.71*** | - |
| | (0.03) | |
| Constant | -1.21*** | -0.34 |
| | (0.23) | (0.47) |
| Time Fixed Effects | Yes | Yes |
| State Fixed Effects | Yes | Yes |
| Pseudo R-squared | 0.23 | 0.21 |

Standard errors in parentheses

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

Table 3: Average Duration in the U.S.

| Years of | Legal Status | | Gender | |
|---|---|---|---|---|
| Education | Illegal | Legal | Male | Female |
| 0-4 | 2.67 | 7.98 | 2.92 | 6.30 |
| 5-8 | 2.70 | 7.13 | 3.19 | 4.74 |
| 9-11 | 3.20 | 6.69 | 3.51 | 4.46 |
| 12 | 3.41 | 8.02 | 3.85 | 6.12 |
| 13+ | 3.58 | 9.00 | 4.00 | 7.27 |

Average duration (in years) of each move to the U.S.

Table 4: Average Wages

| | | U.S. | |
|---|---|---|---|
| Years of Education | Mexico[a] | Illegal[b] | Legal[c] |
| 0-4 | 1.62 | 6.82 | 8.29 |
| 5-8 | 2.03 | 6.90 | 8.65 |
| 9-11 | 2.28 | 6.92 | 9.02 |
| 12 | 2.85 | 7.00 | 10.63 |
| 13+ | 4.90 | 7.38 | 13.44 |

Hourly wages, in 2000 dollars.

[a]: Data from Mexico's labor force survey, 2006.

[b]: Data from the Mexican Migration Project, 1995-2004.

[c]: CPS data. 1980-2004 average

Table 5: Wage Regressions

| | In the U.S. (illegal)[a] | In the U.S. (legal)[b] | In Mexico[c] |
|---|---|---|---|
| 5-8 years education | 0.22** | -0.72*** | 0.36*** |
| | (0.11) | (0.08) | (0.003) |
| 9-11 years education | 0.66*** | 0.03 | 0.68*** |
| | (0.13) | (0.06) | (0.003) |
| 12 years education | 0.56*** | 1.99*** | 1.14*** |
| | (0.19) | (0.07) | (0.004) |
| 13+ years education | 0.81*** | 4.84*** | 2.17*** |
| | (0.24) | (0.07) | (0.003) |
| Age[d] | 0.43* | 6.41*** | 1.21*** |
| | (0.26) | (0.10) | (0.004) |
| Age-squared[d] | -0.09** | -0.67*** | -0.13*** |
| | (0.04) | (0.01) | (0.001) |
| Male | 0.94*** | 2.46*** | 0.63*** |
| | (0.12) | (0.03) | (0.002) |
| Family in U.S. | 0.10 | - | - |
| | (0.10) | | |
| Constant | 5.46*** | -3.46*** | -1.57*** |
| | (0.56) | (0.20) | (0.01) |
| Time Fixed Effects | Yes | Yes | Yes |
| State Fixed Effects | Yes | Yes | Yes |
| R-squared | 0.08 | 0.18 | 0.28 |
| Number of Observations | 5,740 | 115,853 | 2,247,206 |

Standard errors in parentheses

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

[a]: MMP data, [b]: U.S. CPS data, [c] Mexico labor force survey data (ENOE)

[d] Age divided by 10.

Table 6: Transitions into Legal Status

| | |
|---|---|
| 5-8 Years Education | 0.19** |
| | (0.08) |
| 9-11 Years Education | 0.10 |
| | (0.08) |
| 12 Years Education | 0.23** |
| | (0.09) |
| 13+ Years Education | 0.19* |
| | (0.11) |
| Family | 0.28*** |
| | (0.05) |
| Male | 0.08 |
| | (0.05) |
| In U.S. | 1.62*** |
| | (0.06) |
| IRCA | 0.16 |
| | (0.13) |
| IRCA*in U.S. | 0.27* |
| | (0.14) |
| Constant | -3.74*** |
| | (0.09) |
| Pseudo R-squared | 0.36 |

Standard errors in parentheses

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

Table 7: Utility Parameter Estimates

| | |
|---|---|
| Wage Term | 0.15 |
| | (0.0036) |
| Home Bias | 0.24 |
| | (0.0024) |
| With Spouse | 0.22 |
| | (0.014) |
| Family in U.S. | 0.18 |
| | (0.0075) |
| Probability (mover type) | 0.51 |
| | (0.012) |
| Log-likelihood | -49,070.49 |

Standard errors in parentheses.

Table 8: Moving Cost Estimates

| | Mexico to US | Return Migration | Internal Migration |
|---|---|---|---|
| Fixed cost for men | 11.21 | -2.93 | 2.18 |
| | (0.36) | (0.33) | (0.076) |
| Fixed cost for women | 11.60 | -1.86 | 2.26 |
| | (0.38) | (0.079) | (0.079) |
| Distance[a] | 1.07 | -0.79 | 0.47 |
| | (0.040) | (0.046) | (0.031) |
| Age | 0.47 | -0.46 | 0.13 |
| | (0.020) | (0.021) | (0.0031) |
| Population Size[b] | 0.0007 | -0.0072 | -0.0061 |
| | (0.0002) | (0.0006) | (0.0007) |
| Distance to Railroad | 0.083 | | |
| | (0.016) | | |
| 5-8 Years Education | -0.14 | | |
| | (0.06) | | |
| 9-11 Years Education | 0.16 | | |
| | (0.065) | | |
| 12 Years Education | 0.29 | | |
| | (0.081) | | |
| 13+ years education | 0.51 | | |
| | (0.10) | | |

Standard errors in parentheses. [a]:Distance measured in 1000's of miles. [b]: Population divided by 100,000.

Table 9: Illegal Immigration Parameter Estimates

| | |
|---|---|
| Enforcement | 0.027 |
| | (0,0048) |
| Fixed cost | 0.92 |
| | (0.10) |
| Crossing Point Fixed Costs | |
| El Paso, TX | -0.77 |
| | (0.11) |
| San Diego, CA | -3.85 |
| | (0.10) |
| Laredo, TX | 0.11 |
| | (0.11) |
| Rio Grande Valley, TX | -0.025 |
| | (0.11) |
| Tucson, AZ | -1.78 |
| | (0.96) |
| El Centro, TX | -1.33 |
| | (0.11) |

Standard errors in parentheses. Enforcement measured in 10,000 man-hours.

Table 10: Model Fit

| | Data | Model |
|---|---|---|
| Percent that move | 20.7% | 18.3% |
| Number of moves per migrant | 1.31 | 1.42 |
| Years per move | 3.64 | 3.30 |

Table 11: Annual Migration Rates

| Years of Education | Family in U.S. | No family in U.S. |
|---|---|---|
| 0-4 | 4.07% | 1.56% |
| 5-8 | 5.54% | 1.85% |
| 9-11 | 5.49% | 1.42% |
| 12 | 4.23% | 1.01% |
| 13+ | 1.76% | 0.55% |

For a 30 year old primary mover in 2004, living in his home location of Guanajuato, and who cannot move to the U.S. legally

Table 12: Annual Return Migration Rates

| | Spouse in Mexico | | Spouse in U.S. | |
|---|---|---|---|---|
| Years of Education | Family in U.S. | No family in U.S. | Family in U.S. | No family in U.S. |
| 0-4 | 21.41% | 33.71% | 16.28% | 28.51% |
| 5-8 | 20.53% | 34.17% | 15.65% | 29.13% |
| 9-11 | 15.86% | 31.40% | 11.36% | 26.06% |
| 12 | 16.04% | 33.96% | 11.42% | 28.79% |
| 13+ | 21.38% | 39.82% | 16.11% | 35.05% |

For a 30 year old primary mover who lives in California in 2004 and is an illegal immigrant.

Table 13: Counterfactuals – Annual Migration Rates

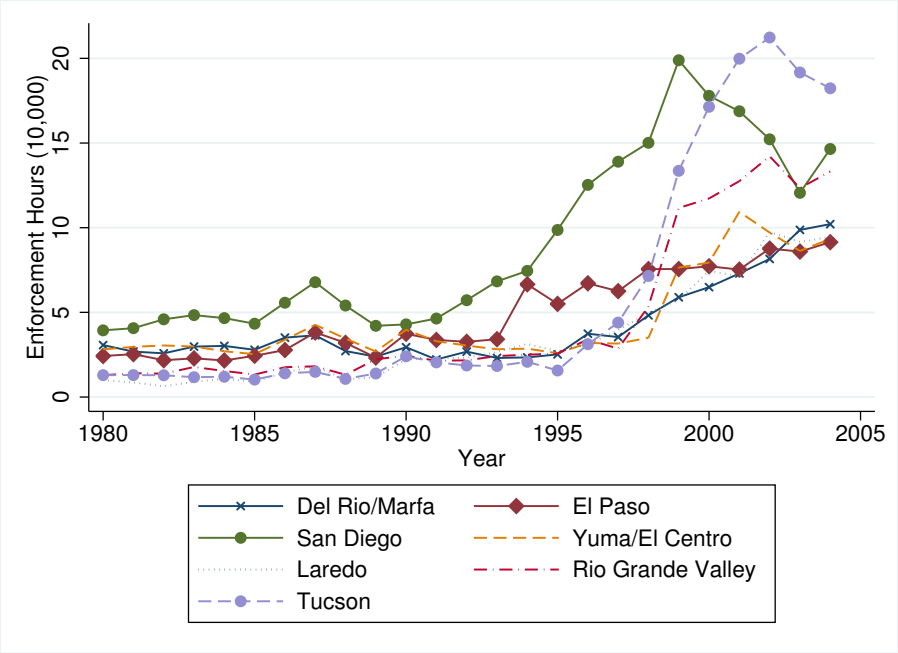
| | Mexico to U.S. Migration Rate | Return Migration Rate |
|---|---|---|
| Baseline | 5.54% | 20.53% |
| Mexican wages up 10% | 4.71% | 21.74% |
| Enforcement up 50% (uniform) | 4.48% | 19.68% |
| Enforcement up 50% (equal costs) | 2.76% | 18.17% |
| Never legal | 3.55% | 25.63% |
| 10% deportation rate | 3.33% | 16.08% |

For a 30 year old primary mover in 2004 who is an illegal immigrant, has family in the U.S., whose wife is living in Mexico, and has 5-8 years of education.

Table 14: Counterfactuals – Lifetime Behavior

| | Percent that move | Moves per migrant | Years per Move | Years in U.S. per person |
|---|---|---|---|---|
| Baseline | 18.29% | 1.42 | 3.30 | 0.86 |
| 10% increase in Mexican wages | 17.47% | 1.42 | 3.20 | 0.79 |
| 50% increase in enforcement | 17.42% | 1.40 | 3.36 | 0.82 |
| 50% increase in enforcement (equal costs) | 16.07% | 1.36 | 3.46 | 0.76 |
| Never Legal | 17.34% | 1.42 | 3.19 | 0.76 |
| 10% deportation rate (beliefs) | 14.33% | 1.40 | 2.94 | 0.59 |

Figure 1: Hours Patrolling the Border



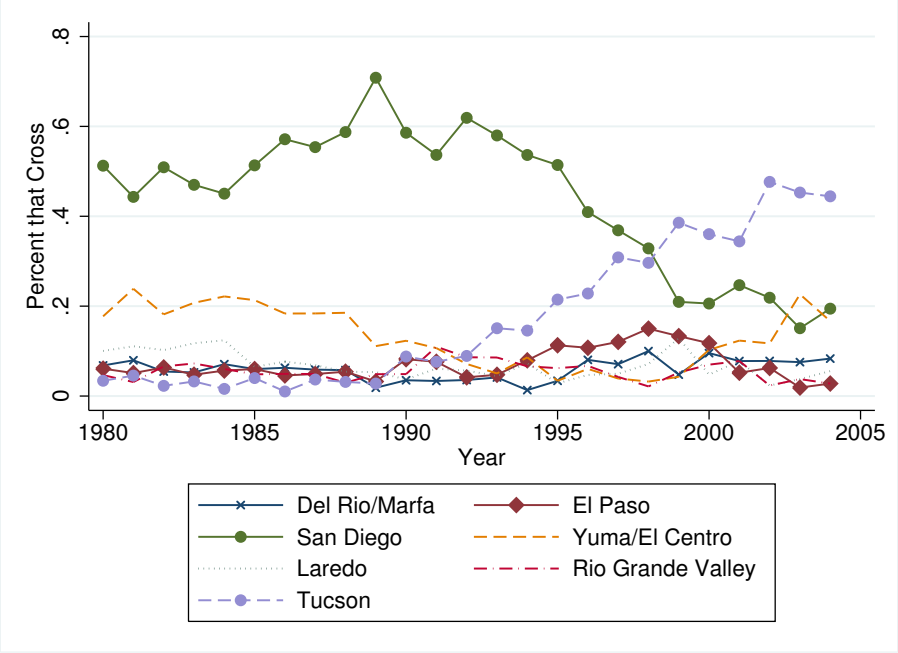


Figure 2: Border Crossing Locations (MMP)