MEXICO-US IMMIGRATION: EFFECTS OF WAGES AND BORDER ENFORCEMENT

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Abstract

In this paper, I study how relative wages and border enforcement affect immigration from Mexico to the United States. To do this, I develop a discrete choice dynamic programming model where people choose from a set of locations in both the US and Mexico, while accounting for the location of one's spouse when making decisions. I estimate the model using data on individual immigration decisions from the Mexican Migration Project. Counterfactuals show that a 10% increase in Mexican wages reduces migration rates and durations, overall decreasing the number of years spent in the US by about 5%. A 50% increase in enforcement reduces migration rates and increases durations of stay in the US, and the overall effect is a 7% decrease in the number of years spent in the US.

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1. Introduction

Approximately 11 million Mexican immigrants were living illegally in the United States in 2015 (Krogstad, Passel, and Cohen, 2017). This large migrant community affects the economies of both countries. For example, migrants send remittances back home, which support development in Mexico.[1] In the US, 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). This was a major issue in the 2016 presidential election, where President Trump campaigned on the promise of a wall between the two countries to cut down on illegal immigration. Despite these large concerns about illegal immigration from Mexico, much about the individual decisions and mechanisms remains poorly understood.

In this paper, I study how wage differentials and US border enforcement affect an individual's immigration decisions. Given the common pattern of repeat and return migration in the data, changes in policy affect both current and future decisions. For example, increased enforcement not only reduces initial migration rates, but also increases the duration of stay in the US by making it more costly for people to come back to the US after returning home. To capture such intertemporal effects, I analyze this problem in a dynamic setting where people choose from multiple locations each period, following Kennan and Walker (2011).[2]

The model extends Kennan and Walker (2011)'s framework in two dimensions. First, I allow for moves across an international border, where people choose from a set of locations which includes both states in the US and in Mexico, necessitating different treatment of illegal and legal immigration. By observing individual legal status, where illegal immigrants crossed the border, and US border enforcement, which varies across locations and time, I can capture various trade-offs of immigration decisions.

Second, I allow for interactions within the decisions of husbands and wives. The data show that this is important, in that 5.7% of women with a husband in the US move each year, compared to on overall female migration rate of 0.6%, suggesting a positive utility of living in the same place.[3] Therefore, a married man living in the US alone will consider the likelihood that his wife will join him, which is endogenous given that

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

[2] Hong (2010) applies a similar framework to Mexico-US immigration, focusing on the legalization process.

[3] Cerrutti and Massey (2001) find that women usually move to the US 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.

she also makes active decisions. This affects reactions to the policy environment. For example, as enforcement increases, a married man living in the US alone knows that his wife is less likely to join him, giving him an extra incentive to return to Mexico. To capture these types of mechanisms, we need a model that allows for interactions within married couples.

The most similar paper on Mexico-US immigration is Thom (2010), who estimates a dynamic migration model where men choose which country to live in, focusing on savings decisions as an incentive for repeat and return migration.[4] In comparison, in my model, people choose from multiple locations in both countries, allowing for both internal and international migration. I also allow for a relationship between the decisions of married couples, enabling me to study how family interactions affect the counterfactual outcomes. Gemici (2011) studies family migration by estimating a dynamic model of migration decisions with intra-household bargaining using US data. In her model, married couples make a joint decision on where to live together, whereas the data from Mexico show that couples often live in different locations.

In this paper, I estimate a discrete choice dynamic programming model where individuals choose from a set of locations in Mexico and the US in each period. Individuals' choices depend on the location of their spouse. To make this computationally feasible, I model household decisions in a sequential process: first, the household head picks a location, and then the spouse decides where to live. The model differentiates between legal and illegal immigrants, who face different moving costs and a different wage distribution in the United States.[5] Border enforcement, measured as the number of person-hours spent patrolling the border, affects the moving cost only for illegal immigrants. 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 border and over time. In the model, individuals who move to the US illegally also choose where to cross the border. The data show that as enforcement at the main crossing point increased, migrants shifted their behavior and crossed at alternate points.[6] Past work, which for the most part uses aggregate enforcement levels, misses this component of the effect of

[4] Another paper that looks at savings decisions is Adda, Dustmann, and Gorlach (2015), who develop a lifecycle model where migrants decide optimal migration lengths, along with savings and investment in human capital. They estimate this model using panel data on immigrants to Germany, and study the relationship between return migration intentions and human capital investments. In comparison to my work, this paper studies the decisions of migrants after they enter the host country.

[5] Kossoudji and Cobb-Clark (2000) and Kossoudji and Cobb-Clark (2002) find that illegal immigrants receive lower wages than legal immigrants and are less likely to work in high-skill occupations when in the US.

[6] 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.

increased border patrol on immigration decisions.

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, finding that increases in Mexican wages decrease both immigration rates and the duration of stays in the US. A 10% increase in Mexican wages reduces the average number of years that a person lives in the US by about 5%.

Estimation of a dynamic model captures mechanisms that could not be studied in a static model. As enforcement increases, fewer people move, but those that do are more reluctant to return home, knowing that it will be harder to re-enter the US in the future. This increases the duration of stays in the US. Policy changes also have differential effects with marital status. As enforcement increases, it becomes harder for women to join their husbands in the US, giving married men an extra incentive to return home, and thereby pushing their migration durations downwards. I hold female migration rates constant in the counterfactual to isolate this effect, and then see an even larger increase in men's durations of stay in the US. Overall, 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 US over a lifetime by approximately 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 US per person would decrease by about 7%. Following US policy changes in the 1990s, most new resources were allocated to certain points along the border, and this research suggests that this is the optimal policy from the perspective of reducing illegal immigration rates.

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 the paper.

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 US 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. In my model, the value of a location depends on expected earnings there, allowing for wage differentials to affect migration decisions. I can quantify how responsive migration decisions are to changes in the wage distribution.

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 US. Espenshade (1990, 1994) finds that there was a decline in apprehensions at the US 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, and some of the past literature has looked at this. Angelucci (2012), using the MMP data, finds that border enforcement affects initial and 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.

The model in this paper allows for an individual's characteristics to affect migration decisions. Past literature has studied this, mostly in a static setting, to understand what factors are important. I build on this work by including the relevant characteristics found to impact migration decisions in my dynamic setting. There is a large literature on the selection of migrants, starting with the theoretical model in Borjas (1987), which predicts that migrants will be negatively selected. This is empirically supported in Ibarraran and Lubotsky (2005). However, Chiquiar and Hanson (2005) find that Mexican immigrants in the US are more educated than non-migrants in Mexico. They find evidence of intermediate selection of immigrants, as do Lacuesta (2006) and Orrenius and Zavodny (2005). Past work also looks at the determinants of the duration of stays in the US; for example, see Reyes and Mameesh (2002), Massey and Espinosa (1997), and Lindstrom (1996).

3. Model

The basic structure of the model follows Kennan and Walker (2011), where each person chooses where to live each period. The value of living in a location depends on the expected wages there, as well as the cost of moving. Since the model is dynamic, individuals also consider the value of being in each location in future periods. At the start of a period, each person sees a set of payoff shocks to living in each location, and then chooses the location with the highest total valuation. The shocks are random, independent and identically distributed (i.i.d.) across locations and time, and unobserved by the econometrician. I assume that the payoff shocks follow a type I extreme value distribution, and solve the model following McFadden (1973) and Rust (1987). I assume a finite horizon, so the model can be solved using backward induction. The model extends Kennan and Walker (2011)'s framework in two dimensions: (1) by allowing for moves across an international border, which necessitates different treatment of illegal and legal immigration, and (2) modeling the interactions within married couples.

The model includes elements to account for the fact that people are moving across an international border, which is different than domestic migration in a couple of important ways. When deciding where to live, people choose from a set of locations, defined as states, in both the US and in Mexico. Migration decisions are substantially affected by whether or not people can move to the US legally, and to account for this, the model differentiates between legal and illegal migrants. Legal immigration status is assumed to be exogenous to the model, and people can transition to legal status in future periods. Legal immigration status affects wage offers in the US, since we expect that legal immigrants will have access to better job opportunities in the US labor market. In addition, US border enforcement only affects the moving costs for illegal immigrants. I assume that all people who choose to move to the US illegally are successful, so the effects of increased enforcement just come through the increased moving cost.[7] This is due to an increased cost of hiring a smuggler (Gathmann, 2008) or an increase in the expected number of attempts before successfully crossing. Illegal immigrants moving to the US choose both a location and a border crossing point, where the cost of moving varies at each crossing point due to differences in the fixed costs and enforcement levels at each point.[8]

In this paper, I also extend Kennan and Walker (2011)'s framework by allowing for the decisions of married individuals to depend on where their spouse is living. Decisions are made individually, but utility depends on whether a person is in the same location as his spouse. Since individuals' 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.

[7] 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 US again.

[8] I assume that once an illegal immigrant enters the US, there is no chance that he will be deported. Espenshade (1994) finds that only 1–2% of illegal immigrants living in the US are caught and deported in each year.

For each household, I define a primary and a secondary mover, which empirically is the husband and wife, respectively. In each period, the primary mover picks a location first, so he does not know his spouse's location when he makes this choice. After the primary mover makes a decision, the secondary mover learns her payoff shocks and decides where to live.[9] This setup allows for people to make migration decisions that are affected by the location of their spouse. Single people's decisions are not affected by a spouse, but they can transition over marital status in future periods, and therefore know that at some point they could have utility differentials based on their spouse's location.

In the remainder of this section, I describe a model without any unobserved heterogeneity. In the estimation, there will be three sources of unobserved heterogeneity, over (1) moving costs, (2) wages in the US, and (3) whether or not women choose to participate in the labor market. This is explained in more detail when I discuss the estimation in Section 6.

3.1 Model Setup

Primary and secondary movers. I solve separate value functions for primary and secondary movers, denoted with superscripts 1 and 2, respectively. In the empirical implementation, men are the primary movers, and women are the secondary movers. A married person's decisions depend on the location of his spouse, whose characteristics I denote with the superscript s. Single men and women make decisions as individuals, but know that they could become married in future periods. I account for these differences by keeping track of marital status m_t, where $m_t = 1$ is a married person and $m_t = 2$ is a single person.

State variables. People learn their legal status at the start of each period. I assume that once a person is able to immigrate legally, this option remains with that person forever. I use z_t to indicate whether or not a person can move to the US legally, where $z_t = 1$ means a person can move to the US legally and $z_t = 2$ means that he cannot.

State variables also include a person's location in the previous period (ℓ_{t-1}), their characteristics X_t, and their marital status m_t. When a married secondary mover picks a location, the primary mover has already chosen where to live in that period, so the

[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 the state space would have to contain the location of the husband and wife. Technically, the state space in my model also contains the locations of both individuals, but using my framework I am able to make certain assumptions that substantially reduce the state space and make the problem computationally feasible. These assumptions are explained in Section 6.4.

location of the spouse (ℓ_t^s) is known and is part of the state space. For the primary mover, who makes the first decision, the location of the spouse in the previous period (ℓ_{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 also part of the state space. To simplify notation, denote Δ_t as the characteristics and legal status of an individual and his spouse, so $\Delta_t = \{X_t, z_t, X_t^s, z_t^s\}$.

Choice set. Denote the set of locations in the US as J_U, those in Mexico as J_M, and the set of border crossing points as C. If moving to the US illegally, a person has to pick both a location and a border crossing point. Denote the choice set as $J(\ell_{t-1}, z_t)$, where

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

Payoff shocks. I denote the set of payoff shocks at time t as $\eta_t = \{\eta_{jt}\}$, where j indexes locations. I assume that these follow an extreme value type I distribution.

Utility. The utility flow depends on a person's location j, characteristics X_t, legal status z_t, marital status m_t, and spouse's location ℓ_t^s, and it is written as $u(j, X_t, z_t, m_t, \ell_t^s)$. This allows for utility to depend on wages, which are a function of a person's characteristics and location. Utility also depends on whether or not a person is at his home location, and increases for married couples who are living in the same place.

Moving costs. The moving cost depends on which locations a person is moving between, and that person's characteristics and legal status. I denote the cost of moving from location ℓ_{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 transitions over legal status, spouse's location for married couples, and marital status for people who are single.[10] The primary mover is uncertain of his spouse's location in the current period. For example, if he moves to the US, he is not sure whether or not his wife will follow. The secondary mover knows her spouse's location in the current period, but is unsure of her spouse's location in the next period. For example, she may move to the US to join her husband, but does not know whether or not he will remain there in the next period. Single people can get married in future periods. Furthermore, if someone gets married, he does not know where his new spouse will be living. Marrying someone who is living in the US will affect decisions differently than marrying someone who is in Mexico.

[10] I do not allow for any expectations of divorce in the model.

For the primary mover, denote the probability of being in the state with legal status z_{t+1}, marital status m_{t+1}, and having a spouse in location ℓ_t^s in this period as $\rho_t^1(z_{t+1}, m_{t+1}, \ell_t^s | j, \Delta_t, m_t, \ell_{t-1}^s)$. This depends on his location j, his characteristics, as well as his marital status and his spouse's previous-period location (if married). For the secondary mover, the transition probability is written as $\rho_t^2(z_{t+1}, m_{t+1}, \ell_{t+1}^s | j, \Delta_t, m_t, \ell_t^s)$.

3.2 Value Function

In this section, I derive the value functions for primary and secondary movers. Because the problem is solved by backward 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 secondary mover's state space includes her previous-period location, her characteristics and those of her spouse, her marital status, and the location of her spouse. After seeing her payoff shocks, she chooses the location with the highest value:

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

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

The deterministic component of living in a location consists of the flow payoff plus the discounted expected value of living there at the start of the next period:

$$\begin{aligned} v_t^2(\cdot) \;\; &= \;\; \tilde{v}_t^2(j, \ell_{t-1}, \Delta_t, m_t, \ell_t^s) + \beta \sum_{z_{t+1}, m_{t+1}, \ell_{t+1}^s} \Big(\rho_t^2(z_{t+1}, m_{t+1}, \ell_{t+1}^s | j, \Delta_t, m_t, \ell_t^s) \\ &\times \;\; E_\eta \left[V_{t+1}^2(j, \Delta_{t+1}, m_{t+1}, \ell_{t+1}^s, \eta_{t+1}) \right] \Big) \, . \end{aligned} \tag{3}$$

The flow payoff of living in location j, denoted as $\tilde{v}_t(\cdot)$, consists of utility net of moving costs, and is defined as

$$\tilde{v}_t^2(j, \ell_{t-1}, \Delta_t, m_t, \ell_t^s) = u(j, X_t, z_t, m_t, \ell_t^s) - c_t(\ell_{t-1}, j, X_t, z_t). \tag{4}$$

The second part of the deterministic component in equation (3) is the expected future value of living in a location. The transition probabilities, written as $\rho^2(\cdot)$, are over legal status, marital status, and location of primary mover. I integrate out the future payoff shocks using the properties of the extreme value distribution, following McFadden (1973) and Rust (1987). For a given legal status, marital status, and location of primary mover, the expected continuation value is given by

$$\begin{aligned} & E_\eta\left[V_{t+1}^2(j, \Delta_{t+1}, m_{t+1}, \ell_{t+1}^s, \eta_{t+1})\right] \\ & = E_\eta\left[\max_{k \in J(j, z_{t+1})} v_{t+1}^2(k, j, \Delta_{t+1}, m_{t+1}, \ell_{t+1}^s) + \eta_{k,t+1}\right] \\ & = \log\left(\sum_{k \in J(j, z_{t+1})} \exp\left(v_{t+1}^2(k, j, \Delta_{t+1}, m_{t+1}, \ell_{t+1}^s)\right)\right) + \gamma\,, \end{aligned} \tag{5}$$

where γ is Euler's constant ($\gamma \approx 0.58$).

I calculate the probability that a person will choose location j at time t, which will be used for two purposes. First, this is the choice probability, necessary to calculate the likelihood function. Second, the choice probability is used to calculate the transition probabilities for the primary mover, who is concerned with the probability that his spouse lives in a given location in this period. I assume that he has all of the same information as the secondary mover, but since the primary mover makes the first decision, the secondary mover's payoff shocks have not yet been realized, so I can only calculate the probability that the secondary mover will make a given decision.

Since I assume that the payoff shocks are distributed with an extreme value distribution, the choice probabilities take a logit form, again following McFadden (1973) and Rust (1987). The probability that a person picks location j is given by the following formula:

$$P_t^2(j|\ell_{t-1}, \Delta_t, m_t, \ell_t^s) = \frac{\exp\left(v_t^2(j, \ell_{t-1}, \Delta_t, m_t, \ell_t^s)\right)}{\sum_{k \in J(\ell_{t-1}, z_t)} \exp\left(v_t^2(k, \ell_{t-1}, \Delta_t, m_t, \ell_t^s)\right)}\,. \tag{6}$$

3.2.2 Primary Movers

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

$$V_t^1(\ell_{t-1}, \Delta_t, m_t, \ell_{t-1}^s, \eta_t) = \max_{j \in J(\ell_{t-1}, z_t)} v_t^1(j, \ell_{t-1}, \Delta_t, m_t, \ell_{t-1}^s) + \eta_{jt}\,. \tag{7}$$

In comparison to the secondary mover, the primary mover does not know where his spouse is living in this period, and only knows her previous-period location ℓ_{t-1}^s.

As before, the deterministic component of living in a location includes the flow utility and the expected continuation value. However, in this case, I do not know the exact flow utility, since the secondary mover's location has not been determined. I instead calculate the expected flow utility:

$$E_{\ell_t^s}\left[\tilde{v}_t(j,\ell_{t-1},\Delta_t,m_t,\ell_t^s)|\ell_{t-1}^s\right] = \sum_{k\in J(\ell_{t-1},z_t)} P_t^2(k|\ell_{t-1}^s,\Delta_t^s,m_t^s,j)u(j,X_t,z_t,m_t,k) - c(\ell_{t-1},j,X_t,z_t)\,. \tag{8}$$

This is calculated using the probability $P_t^2(\cdot)$ that the secondary mover will pick a given location, defined in equation (6).

Denoting the transition probabilities as $\rho^1(\cdot)$, I can write the deterministic component of living in a location as:

$$\begin{aligned} v_t^1(\cdot) &= E_{\ell_t^s}\left[\tilde{v}_t(j,\ell_{t-1},\Delta_t,m_t,\ell_t^s)|\ell_{t-1}^s\right] + \beta \sum_{z_{t+1},m_{t+1},\ell_t^s}\Big(\rho_t^1(z_{t+1},m_{t+1},\ell_t^s|j,\Delta_t,m_t,\ell_{t-1}^s) \\ &\times\ E_\eta\left[V_{t+1}^1(j,\Delta_{t+1},m_{t+1},\ell_t^s,\eta_{t+1})\right]\Big)\,. \end{aligned} \tag{9}$$

For a given state, the continuation value is calculated by integrating over the distribution of future payoff shocks:

$$\begin{aligned} & E_\eta\left[V_{t+1}^1(j,\Delta_{t+1},m_{t+1},\ell_t^s,\eta_{t+1})\right] \\ =\ & E_\eta\left[\max_{k\in J^1(j,z_{t+1})} v_{t+1}^1(k,j,\Delta_{t+1},m_{t+1},\ell_t^s) + \eta_{j,t+1}\right] \\ =\ & \log\left(\sum_{k\in J(j,z_{t+1})} \exp v_{t+1}^1\Big(k,j,\Delta_{t+1},m_{t+1},\ell_t^s)\Big)\right) + \gamma\,. \end{aligned} \tag{10}$$

I calculate the probabilities that the primary mover picks each location in a period, which are used to calculate the likelihood function. They also are a part of the transition probabilities for the secondary mover. Using the properties of the extreme value distribution, the probability that a primary mover picks location j is given by

$$P_t^1(j|\ell_{t-1},\Delta_t,m_t,\ell_{t-1}^s) = \frac{\exp\Big(v_t^1(j,\ell_{t-1},\Delta_t,m_t,\ell_{t-1}^s)\Big)}{\sum_{k\in J(\ell_{t-1},z_t)}\exp\Big(v_t^1(k,\ell_{t-1},\Delta_t,m_t,\ell_{t-1}^s)\Big)}\,. \tag{11}$$

3.2.3 Transition Probabilities

In this section, I calculate the transition probabilities. There is uncertainty over future legal status, future marital status (if single), and the location of one's spouse (if married).

I assume that the probability that a person has a given legal status in the next period depends on his characteristics and his current legal status.[11] For people who are married, the transition probabilities are also over a spouse's future decisions. I assume that the agent has the same information as the spouse about the spouse's future decisions. This means that the probability that a person's spouse lives in a given location is given by his choice probabilities. A single person can become married in future periods with some probability. If he gets married, there is also uncertainty over where his new spouse is living.

Recall that $\rho^1(\cdot)$ and $\rho^2(\cdot)$ are the transition probabilities for primary and secondary movers. These give the probability that a person has a given legal status, marital status, and if married, has a spouse living in a certain location in the next period.

$$\rho^1_t(z_{t+1}, m_{t+1}, \ell^s_t | \ell_t, \Delta_t, m_t, \ell^s_{t-1}) = \begin{cases} \delta(z_{t+1}|z_t, X_t) P^2_t(\ell^s_t | \ell^s_{t-1}, \Delta^s_t, m^s_t, \ell_t) & \text{if } m_t = 1 \\ \delta(z_{t+1}|z_t, X_t) \psi^1(m_{t+1}, \ell^s_t | X_t, \ell_t) & \text{if } m_t = 2 \,. \end{cases} \tag{12}$$

$$\rho^2_t(z_{t+1}, m_{t+1}, \ell^s_{t+1} | \ell_t, \Delta_t, m_t, \ell^s_t) = \begin{cases} \delta(z_{t+1}|z_t, X_t) P^1_{t+1}(\ell^s_{t+1} | \ell^s_t, \Delta^s_{t+1}, m^s_{t+1}, \ell_t) & \text{if } m_t = 1 \\ \delta(z_{t+1}|z_t, X_t) \psi^2(m_{t+1}, \ell^s_{t+1} | X_t, \ell_t) & \text{if } m_t = 2 \,. \end{cases} \tag{13}$$

The function $\delta(\cdot)$ gives the probability that a person has a given legal status in the next period. For primary movers, there is uncertainty over where the secondary mover will live in the current period. This is represented by the function $P^2_t(\cdot)$, which comes from the secondary mover's choice probabilities defined in equation (6). Likewise, for secondary movers, there is uncertainty over the primary mover's location in the next period. This is represented by the function $P^1_{t+1}(\cdot)$, which comes from the primary mover's choice probabilities defined in equation (11). Single people could become married in future periods, and the probability of this happening is written as $\psi^k(\cdot)$, with $k = 1, 2$ for primary and secondary movers, respectively. If he gets married, there is a probability his new spouse lives in each location. If he does not get married, then he continues to make decisions as a single person.[12]

[11] I assume that legal status is an absorbing state: once a person is a legal immigrant, he cannot lose the ability to move legally.

[12] In equations (12) and (13), I assume that people who are married will remain so, since there is no chance of their marital status changing.

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, and is still ongoing. The project aims to understand the decisions and outcomes relating to immigration for Mexican individuals. To my knowledge, this is the most detailed source of information on immigration decisions between the US and Mexico, most importantly on illegal immigrants, which are underrepresented in most US-based surveys. The survey asks questions on when and where people lived in the US, how they got across the border, and what the wage outcomes in the US were, which is the set of information necessary to estimate the model detailed in the previous section.

For household heads and spouses, the MMP collects a lifetime migration history, asking people which country and state they lived in each year. This information is used to construct a panel dataset which contains each person's location at each point in time. I also know if and when each person is allowed to move to the US legally. For people who move to the US illegally, the MMP records when and where they cross the border.

The MMP also collects information on the remaining members of the household. The inclusion of these respondents allows me to cover a wider age range than if I were to just use the household head and spouse data. Although the MMP does not ask for the lifetime migration histories for this group, it asks many questions related to migration. The survey asks for the migrants' wages, location, and legal status for their first and last trip to the US, as well as their total number of US trips. For people who have moved to the US two or fewer times, I know their full history of US migration, although when they are in Mexico I may not know their precise location. For people who have moved more than two times, there are gaps in the sample for years when a migration is not reported. I will have to integrate over the missing information to compensate for the lack of full histories for each person.[14] In addition, in this group, I do not know these people's marital status at each point in time, and they are also not matched to a spouse in the data, so I cannot include the marriage interactions component of the model for this group. I call this sample the "partial history" sample, whereas I call the group of household heads and spouses the "full history" sample.

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*

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

[14]In most cases, I at least know the country a person is living in, if not his exact location. In 99% of the person-year observations, I know the country the surveyed people are living in.

Control Act (IRCA). Because the data have lifetime histories, the sample spans many years. 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 6,457 for the full history sample, where I observe each person's location from age 17 until the year surveyed.[15] The partial history sample is larger, consisting of 41,069 individuals.

One downside of the data is that 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 oversampled.[16] Over time, the MMP sampling frame has shifted to other areas in Mexico, thus covering areas with lower migration rates. Because the MMP collects retrospective data, I have information on migration decisions in earlier years in these communities that are surveyed later, mitigating this problem somewhat. Another restriction of the data is that the sample misses permanent migrants, because the survey is administered in Mexico.[17] Therefore, the results of this paper apply to this specific section of the Mexican population. In Appendix A, I compare the MMP sample to the Current Population Study (CPS) (restricting the sample to Mexicans living in the US) and to Mexican census data, to get an understanding of the limitations of the data. Table A1 in Appendix A shows that the MMP sample has substantially more men than the CPS, which is unsurprising due to the prevalence of temporary migrants in the MMP. The CPS sample also has higher levels of education. Table A2 compares the MMP sample to the Mexican census data. The MMP sample is younger, most likely because of my sample selection criteria explained in the previous paragraph. The MMP sample also has higher education levels.

Unlike other data sources, the MMP has wage data when people are in the US illegally, allowing me to estimate the wage distribution for illegal immigrants living in the US. In comparison, other datasets report country of birth but not legal status, and I expect that datasets such as the CPS will be biased towards legal immigrants, since illegal immigrants are likely to avoid government surveys. Because legal immigration is relatively rare in the MMP data, I combine MMP wages with CPS data on Mexicans living in the US to get a larger sample size to study the legal wage distribution. The MMP also records wages in Mexico; however, there are limited wage observations per person and the data give imprecise estimates. Therefore, for Mexican wages, I use data from Mexican labor force

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

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

[17] The MMP attempts to track individuals in the US, but has had limited success, so I do not include these observations.

surveys: the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) in 1989, 1992, and 1994 , and the Encuesta Nacional de Empleo (ENE) from 1995 to 2004.

To measure border enforcement, I use data from US Customs and Border Protection (CBP) on the number of person-hours spent patrolling each sector of the border.[18] CBP divides the US-Mexico border into nine regions, and the data report the person-hours spent patrolling each sector.

5. Descriptive Statistics

Tables 1 and 2 show the characteristics of the sample, divided into five groups: people who move internally, people who move to the US, people who move internally and to the US, non-migrants, and people who can immigrate legally. Table 1 shows this information for the full history sample, and Table 2 for the partial history sample. For the partial history sample, there is no information on internal movers, since the MMP has insufficient information to isolate this group. These tables show that most US migrants are male. Each row shows the percent of a group (i.e., internal movers) with a given level of education. People who move to the US have the least education. The literature finds that returns to education are higher in Mexico than in the US, possibly explaining why educated people are less likely to immigrate. In addition, illegal immigrants do not have access to the full US labor market, and therefore may not be able to find jobs that require higher levels of education. People who can immigrate legally make up close to 3% of the full history sample and about 2.4% of the partial history sample.

5.1 Migration Decisions

Between 1980 and 2004, an average of 2.5% of the people in the sample living in Mexico moved to the US in each year. Table 3 looks at the effects of family interactions on migration rates.[19] The migration behavior of married men is very similar to that of single men. However, there are stark differences in the migration decisions of married and single women. I compare married women whose husband is in the US to single women, and show that these married women have substantially higher migration rates.[20] This suggests that husbands' decisions have an important effect on female migration decisions.

[18] I thank Gordon Hanson for providing these data.

[19] This table only uses the full history sample because I do not have information on marital status at each point in time for the partial history sample.

[20] I do not include married women with a spouse in Mexico in the sample, since their migration rates are close to zero.

To further analyze the determinants of migration decisions, I estimate the probability that a person who lives in Mexico moves to the US in a given year using probit regressions. The marginal effects are reported in Table 5. The first two columns include both genders, and the third and fourth columns allow for separate effects for men and women, respectively.[21] In all regressions but column (4), the effect of age on migration is negative and statistically significant, supporting the human capital model, which predicts that younger people are more likely to move because they have more time to earn higher wages. Using family members as a measure of networks, I find that having a family member in the US makes a person more likely to immigrate. Legal immigrants are more likely to move, as are people who have moved to the US before. Columns (2)–(4) include controls for marital status. Column (2), which includes both men and women, indicates that single men, married men, and married women are more likely to move than single women. Column (3) only includes men, and shows no difference between married and single men. Column (4), which only includes women, again shows that married women whose spouse is in the US are more likely to immigrate than single women. Since married women only move to the US when their husband is in the US, it is important to include these sorts of interactions in a model.[22]

The data on return migration rates show that 9% of all migrants living in the US move to Mexico each year. Raw statistics show that men have higher return migration rates than women. Suspecting that return migration rates for married men are affected by the location of their wives, in Table 4, looking at only men in the full history sample, I split the sample by marital status and wife's location. Married men whose wife is in Mexico are much more likely to return home, whereas those whose wife is living in the US have a much lower return migration rate.

Using a probit regression, I estimate the probability that a person currently living in the US returns to Mexico in a given year. The marginal effects are shown in Table 6. Columns (1) and (2) use data for both genders, and columns (3) and (4) use data for men and women, respectively.[23] All specifications except for column (4) show that that legal immigrants are less likely to return home. Columns (2)–(4) control for marital status, and additionally split the sample for married men based on whether their spouse is living in Mexico or the US. Married men with a wife in Mexico are more likely to return migrate

[21]Columns (2)–(4) control for marital status, and therefore only include data from the full history sample, since I do not know marital status at each point in time in the partial history data.

[22]This regression does not include married women whose spouse is living in Mexico, since I dropped the rare cases where the woman was in the US while the man was in Mexico. This term would not be identified in the regression because this group has 0 migration rates.

[23]Column (1) uses the full and partial history samples, whereas the other columns only use the full history sample.

than single men, whereas married men whose wife is in the US are less likely to return migrate than single men. This suggests that moving home to be with one's spouse is a strong incentive for return migration.

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 US per migrant is 1.64 for men and 1.14 for women , showing that many migrants move more than once.[24] Women move less and are less likely to return migrate, implying that when women move, their decision is more likely to be permanent. The average durations illustrate this more clearly. Overall, the average migration duration is 4.4 years. It is slightly higher for legal than illegal movers (4.83 versus 4.35 years, respectively). The average duration for men is 4.15 years, and the average duration for women is 5.20 years, again indicating that when women move, their decision is more likely to be permanent.

This section shows that it is crucial to allow for a relationship between spouses' decisions. The model in this paper accounts for the following trends observed in the data: (1) women are more likely to move if their husband is in the US, and (2) men are less likely to return migrate if their spouse is living with them in the US. By including both male and female decisions in the model, I can study how their interactions affect the counterfactual outcomes.

A key component of the model is that individuals are choosing from a set of locations in both the US and Mexico, instead of just picking between the two countries. This is an important contribution of this paper, in that most past work on Mexico to US migration does not allow for internal migration. Internal migration is fairly common, as close to 30% of the people in the full history sample moves internally, making it important to allow for people to choose from locations in both countries.[25] Due to these high rates, changes in wages in Mexico, even outside of one's home location, could affect the decision on whether or not to move to the US. The model accounts for this by letting people choose from a set of locations in both countries.

5.2 Border Enforcement

To measure border enforcement, I use data from US Customs and Border Protection (CBP) on the number of person-hours spent patrolling the border. CBP divides the US-Mexico border into nine sectors, as shown in Figure 1, each of which gets a different allocation of

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

[25]The empirical trends on follow what is normally found in the internal migration literature. For example, see Greenwood (1997).

resources each year.[26] Figure 2 shows the number of person-hours spent patrolling each region of the border over time.[27] Relative to the levels observed today, border patrol was fairly low in the early 1980s. 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 1990s.

Much of the variation in Figure 2 can be explained by changes in US policy. The *Immigration Reform and Control Act* of 1986 (IRCA) called for increased enforcement along the US-Mexico border. However, changes in enforcement were small until the early 1990s, when new policies further increased border patrol.[28]

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. 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 50% of illegal immigrants crossed the border at San Diego. This decreased to 27% post-1995. At the same time, the share of people crossing at Tucson increased. 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.[29]

6. Estimation

I estimate the model using maximum likelihood. I assume that a person has 28 location choices, which include 24 locations in Mexico and four in the US. The Mexico locations are loosely defined as states; however, some states are grouped when they border each other

[26] 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.

[27] The data report the levels of patrol on a monthly basis. This graph shows the average for each year. This graph shows seven lines, instead of one line for each of the nine sectors, because in two cases, I combined two sectors that have low activity.

[28] 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 also allocated more resources to border enforcement.

[29] 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 US government uses to monitor the border. Technology such as stadium lighting, infrared cameras, and ground sensors is used to aid border patrol agents. However, border patrol hours are highly correlated with total expenditures on border patrol.

and have smaller sample sizes.[30] The locations in the US are California, Texas, Illinois, and the remainder of states which are grouped into one location choice.[31] I restrict decisions so that a married woman cannot move to the US unless her husband is living there. This simplifies computation, and is empirically grounded since it is very rare in the data for the wife to live in the US while the husband is in Mexico.

Illegal immigrants moving to the US also choose where to cross the border. The US government divides the border into nine 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 seven to avoid this problem.[32] Therefore, an illegal immigrant has 28 choices in the US, the four locations combined with the 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.

There are three sources of unobserved heterogeneity in the model. The first is over moving cost type, and this is at the household level. In particular, I assume that there are two types, where one group (the stayers) has infinitely high moving costs and will never move to the US. The second source of unobserved heterogeneity is over wage outcomes when living in the US, and I assume that this is at the individual level. These values are known by the individual but unobserved by the econometrician. The data show that many women do not work, and therefore would not be affected by wage differentials. To account for this, there is a third set of unobserved heterogeneity that allows for women to be a worker or a non-worker type, where decisions of non-worker types are not affected by wages. I integrate over the probability that a woman is a worker type, which is taken from aggregate statistics on female labor force participation from the World Bank's World Development Indicators.[33]

Identification of the wage parameters and the fixed cost of moving follows the arguments in Kennan and Walker (2011). My model also has the parameters related to illegal immigration, where identification of the border enforcement term comes from compar-

[30]There are 32 Mexican states. Grouping them into 24 locations, by combining nearby states, allows me to speed up computation substantially. The groupings were done by combining nearby states. Table A3 in Appendix A shows sample sizes and which states were combined in the estimation.

[31]I assume that once a person moves to the US, he cannot move to a new location in the US, and can only choose between his current location and all locations in Mexico. This assumption is made because the data show very little movement across US locations.

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

[33]Ideally, I would model the labor supply decisions of women. However, the MMP does not provide yearly labor force decisions, so this is not possible. The MMP provides some wage information. Therefore, if I observe a wage for a woman in the sample, I know she is a worker type. For the others, I have to integrate over these probabilities.

ing the rate that people cross at each border patrol sector over time as enforcement hours are reallocated. The intuition for how these parameters are identified is discussed in Appendix B.

6.1 Wages

I estimate three sets of wage functions: when people are in Mexico, in the US illegally, and in the US legally. For all three situations, wages have a deterministic and a random component, where the latter is realized each period after a person decides where to live. This means that when making migration decisions, people only consider their expected wage in each location.

Wages in Mexico are estimated in a first stage regression. The MMP data do not have sufficient information on individual wages in Mexico, so I cannot learn about how individual variations in wage draws affect migration decisions.[34] Instead, I use data from Mexican labor force surveys, which have more accurate information on Mexican wages in each year, to estimate this wage distribution.

Using data from the ENIGH in 1989, 1992, and 1994 and the ENE from 1995 to 2004, I estimate wage regressions in each year:

$$w_{ijt}^{M} = \beta^{Mt} X_{it} + \gamma_j^{Mt} + \epsilon_{ijt} \,. \tag{14}$$

In equation (14), X_{it} are individual characteristics, β^{Mt} are the returns to these characteristics when in Mexico at time t, and γ^{Mt} are state fixed effects, which also vary over time. The first two columns of Table 7 show the results of the wage regression for Mexican wages in 1989 and 2004, the first and last years where I have these data. The regressions for all years are in Appendix A. There are strong returns to education and experience in these data, which have fluctuated significantly over the time period analyzed. Note that in equation (14), there is no unobserved heterogeneity in wages, so unobserved types are independent of Mexican wages. I make this assumption due to the lack of reliable wage information in the MMP when individuals live in Mexico. Unfortunately, the lack of individual-level heterogeneity over Mexican wages is a limitation of this analysis.

I use the results of year-by-year regressions to calculate an expected wage for each person in each location in Mexico and year. Because I do not have wage data for every year in the estimation, I need to compute expected wages in the missing years. To do this,

[34] There is limited wage information when people are in Mexico. This is for the "last domestic wage" as well as wages for internal migrations in Mexico. However, these wages are often hard to match to specific points in time, and due to severe fluctuations in the Mexican economy, this often leads to imprecise estimates.

I run a wage regression using all of the available data, including time trends in the returns to education, which allows for (1) changes in wage levels over time and (2) changes in the returns to education. The results of this regression are in the third column of Table 7. This allows me to calculate expected wages in Mexico in all years and states, using the year-by-year regressions when possible and the regression with all years of data when I do not have data for that year.

To estimate the model, I also need to make assumptions on people's beliefs on future wages. It is unlikely that people had perfect foresight over what would happen to Mexican wages over this period, especially due to the severe fluctuations in Mexico's economy. To specify wage expectations, I use the results from the wage regression to impute an expected wage for each person in each location and time, denoted as $\hat{w}_{ijt}^{M}$. I assume that people expect there is some chance (denoted as p_{loss}) of a large wage drop (at rate α) in each period that causes them to earn less than this expected wage. [35] Then I can write each person's wage expectations as

$$Ew_{ijt}^{M} = \begin{cases} \hat{w}_{ijt}^{M} & \text{with probability } 1 - p_{loss} \\ (1-\alpha)\hat{w}_{ijt}^{M} & \text{with probability } p_{loss}\ . \end{cases} \tag{15}$$

The probability p_{loss} of this wage drop is given by the fraction of years Mexico experienced negative wage growth. The expected wage drop (α) is equal to the average wage drop in these bad years.

For wages in the US, the parameters are estimated jointly with the moving cost and utility parameters. There is a separate wage process for legal and illegal immigrants, written as

$$w_{ijt}^{ill} = \beta^{ill} X_{it} + \gamma_j^{ill} + \kappa_i^{ill} + \epsilon_{ijt}^{ill} \tag{16}$$

$$w_{ijt}^{leg} = \beta^{leg} X_{it} + \gamma_j^{leg} + \kappa_i^{leg} + \epsilon_{ijt}^{leg}\ . \tag{17}$$

Wages depend on demographic characteristics X_{it}, which include education, gender, age, and whether or not a person has family living in the United States.[36] I include time trends to allow for changes over time, as well as location fixed effects γ_j.[37] The match component, which is the source of unobserved heterogeneity over wages, is written as

[35] These are one-period shocks that do not persist.

[36] Munshi (2003) finds that a Mexican immigrant living in the US is more likely to be employed and to hold a higher paying nonagricultural job if his network is larger. This variable is only available for illegal immigrants, because it is not in the CPS data, which are partially used in the estimation of the wage process for legal immigrants.

[37] These are estimated in a first stage using CPS data due to the small sample sizes in the MMP. For illegal wages, there is just an overall time trend, and for legal wages, the time trends are in the returns to education.

$\kappa_i = \{\kappa_i^{ill}, \kappa_i^{leg}\}$. When estimating these terms, I assume the legal and illegal fixed effects are each drawn from a symmetric three point distribution where each value is equally likely. There is a correlation between the unobserved types of husbands and wives. Each individual knows the value of his fixed effect if he were to move to the US.

For legal immigrants, the MMP only has a small number of observations with wage information, making it difficult to precisely estimate the wage parameters. I combine the MMP wage observations with CPS data to estimate this wage process. I use data on Mexican-born individuals in the CPS, jointly with the MMP wage observations for legal immigrants, to estimate this set of wage parameters.[38] For the CPS data, I do not have information on their migration decisions, so these individuals contribute to the likelihood through just their wages.

6.2 Moving Costs

Here I explain the determinants of moving costs for the mover types in the model. The full parameterization of the moving cost function is explained in Appendix C.

The cost of moving includes a fixed cost, and also depends on the distance between locations, calculated as the driving distances between the most populous cities in each state.[39] The cost of moving also depends on age, which captures other effects of age on immigration that are not accounted for in the model or the wage distribution. The population size of the destination also affects moving costs, to account for the empirical fact that people are more likely to move to larger locations.[40] For people moving to the US, I allow the moving cost to depend on education.

Networks, defined as the people that an individual knows who are already living in the US, can affect the cost of moving to the US for that person.[41] Empirical evidence shows that migration rates vary across states, suggesting 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.[42] When immigration from

[38] This is assuming that all individuals from Mexico in the CPS are legal immigrants. I do not know legal status in the CPS, but assume that all respondents are legal since illegal immigrants should be hesitant to participate in government surveys.

[39] When a person is moving to the US 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 US.

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

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

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

Mexico to the US began in the early 1900s, US employers used railroads to transport laborers 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.

US border enforcement affects the border crossing costs for illegal immigrants. However, there is potential endogeneity in that enforcement at each sector could be affected by the number of migrants crossing there. To account for this, I follow Bohn and Pugatch (2015) and use the enforcement levels, lagged by 2 periods, to predict future enforcement. Budget allocations for border enforcement are typically determined two years ahead of time, although extra resources can be allocated when needed due to unexpected shocks. The two-year-lagged values of border enforcement levels represent the best predictor of future enforcement needs before these shocks hit. This controls for endogeneity of enforcement and migration flows at each sector. This setup assumes perfect foresight, which is a strong assumption. I have estimated the model assuming myopic expectations and the results were similar. The cost of moving through a specific border patrol sector depends on the predicted enforcement levels there, as well as a fixed cost of crossing through that point. 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.

Since the model is dynamic, I need to make assumptions on people's beliefs on future levels of border enforcement. I assume that people have perfect foresight on border enforcement.[43]

6.3 Transition Rates

The transition probabilities defined in Section 3.2.3 are over spouse locations, legal status, and marriage rates. The transitions over spouse's location come from the choice probabilities in the model. The legal status and marriage transition rates come from the data.

Using the MMP data, I estimate the probability that a person switches from illegal to legal status with a probit regression that controls for education, family networks, and gender. I assume the amnesty due to IRCA in 1986 was unanticipated. People could only be legalized under IRCA if they had lived in the US continuously since 1982. Therefore, this policy would only affect immigration decisions if it was anticipated 4–5 years prior to implementation, making this assumption reasonable. The results of this regression, shown in column (1) of Table A7 in Appendix A, indicate that having family in the US

[43] For years past 2004, I assume that people expect enforcement to remain constant in future periods.

and being male strongly affects the probability of being granted legal status. I use the results of this regression to impute a probability that each person is granted legal status, which is used as exogenously-given transition rates when estimating the model.

In the model, single people know that there is some probability that they will get married in future periods. I estimate marriage rates using a probit regression. Column (2) of Table A7 in Appendix A shows how different factors affect the probability of becoming married. I use these results for the transition probabilities in the model estimation.

6.4 Utility Function

Utility depends on a person's expected wage, which is a function of his location and characteristics. A person's utility increases if he is living at his home location, which is defined as the state in which he was born. I allow for utility to increase if a person is in the same country as his spouse. Alternatively, I could have assumed that this depends on being in the same location as one's spouse, but this would significantly increase computation. My methodology only requires me to track the country of his spouse instead of the exact location, and yet still captures the empirical trend that people make migration decisions to be near their spouse.[44] I also allow for higher utility in the US if a person also has family members living there. The full parameterization of the utility function is explained in Appendix C.

6.5 Likelihood Function

In this section, I explain the derivation of the likelihood function; the full details are explained in Appendix D.

I estimate the model using maximum likelihood. I calculate the likelihood function at the household level, where I integrate over the probability that each household is of a specific moving cost type, the probability that each person has a specific wage fixed effect, and the probability that the woman is a worker type.[45]

For each household, I observe a history of location choices for the primary and secondary mover. These choices depend on moving cost type τ, where I assume there are

[44] Keeping the location of the spouse in the state space would mean that the state space has 28^2 elements regarding location, for a person's location as well as his spouse, which would be quite slow to compute. Using country instead of location allows me to capture the empirical trends of interest.

[45] I only include married couples as part of the same household, for in this case the likelihood is at the household level due to the joint nature of migration decisions in the model. Many households start as unmarried but become married in a future period. In the estimation, I calculate the likelihood at the household level, where each person makes decisions as a single agent before getting married, and then the couple's decisions relate to one another once married.

mover and stayer types, where the stayer types have infinitely high costs of moving to the US. Women can be worker or non-worker types, where utility for the non-worker types is not affected by wages. For each person, I observe wage draws when in the US. There is unobserved heterogeneity in the wage draws. These are individual specific terms, known by every member of the household and unobserved by the econometrician. I allow for a correlation between the unobserved types of husbands and wives.

First, I explain how I calculate the likelihood function conditional on moving cost type and wage type. The migration probabilities for each period come from the choice probabilities defined in equations (11) and (6). For secondary movers, I differentiate between the choice probabilities for worker and non-worker types, where the utility for non-worker types is not affected by wages. I calculate the probability of seeing an observed history for a household when the woman is a worker type and when she is a non-worker type. I then integrate over the probability that the woman is a worker type.

The previous explanation was for calculating the likelihood conditional on moving cost and wage type. To calculate the full likelihood, I have to incorporate the probability that a household has moving cost type τ and each individual has a given wage type. I estimate the probability that a household has moving cost type τ. I allow for a correlation between the types of husbands and wives, by estimating the probability that a woman with a given wage-type is married to a man with a given type. This allows for assortative matching in the labor market, if the estimates reveal that a high-wage-type man is most likely to be married to a high-wage-type woman.[46]

7. Results

Table 8 reports the utility parameter estimates.[47] The results show that people prefer to live at their home location, and that men living in the same location as their spouse have higher utility. There is no statistically significant effect for women, which can be explained due to the assumptions in the model. Because women rarely move to the US without their husband, I assumed that a married woman cannot live in the US unless her husband is there. Without this assumption, I would get a much larger preference for living in the same location as one's spouse for women, since women do not move to the US without their husbands. In addition, people with family in the US have higher utility when living in the US than those who do not. There are mover and stayer types in the model; the

[46]The parameters are fixed so that the total probability that a man or a woman is each type is set at 1/3. This gives a system of equations for the match probabilities. Even though there are nine parameters, I only have to estimate four and then the remainder are pinned down.

[47]Appendix E discusses computational issues.

estimation is set so that the fixed cost of moving to the US 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 close to 70%.

In a separate exercise, 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.[48] This shows that the inclusion of this part of the model substantially improves its ability to model decisions.

Table 9 shows the parameters of the immigrant wage distribution, for both legal and illegal immigrants. There are stronger returns to education for legal immigrants than for illegal immigrants, reflecting that high-skilled legal immigrants can access jobs that reward these skills.[49] The age profile has the standard concave shape for legal immigrants. For illegal immigrants, wages increase slightly at young ages, but then decrease. For the age range that comprises most of the sample, the wage profile is essentially flat, since the steeper drop-off in wages does not begin until older ages.

Table 10 shows the moving cost parameters (excluding the parts related to illegal immigration). There are three moving cost functions: Mexico to US migration, return migration, and internal migration. The first component of the moving cost is the fixed cost of moving, which I allow to vary with gender. The moving cost also depends on the distance between locations. For Mexico to US (legal) migration, the cost increases in distance, as expected, and I do not see a statistically significant effect of distance on internal migration decisions. 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.[50] This behavior is most likely driving this parameter estimate. Moving costs also depend on population size, in that I would expect people to be more likely to move to larger locations.[51] For internal migration, the moving cost decreases with population size, indicating that people are more likely to move to larger locations. For Mexico to US migration, the effect is positive but small. Population size is perhaps not an accurate proxy in this case, since migrants may care more about the number of people from their community in a

[48] This was rejected using a significance level of 0.01.

[49] The estimated parameters are for a static distribution, but the wages do change over time. The time trends in wages are estimated in a first stage and inputted into the model. For illegal wages, there is a constant time trend. For legal wages, the time trend depends on education. The state fixed effects are also estimated in a first stage.

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

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

location than the total population size.

Table 11 shows the parameter estimates relating to illegal immigration. Distance increases the cost of moving, where the distance is calculated as the distance from the Mexican state to the crossing point plus the distance from the crossing point to the US destination. This allows for the location choices and crossing point decisions to be related. 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.

7.1 Model Fit

To look at the model fit, I first show statistics on annual Mexico to US and return migration rates, comparing the values in the data to model predictions. The first row of Table 12 shows the whole sample, and the second two rows split the sample by legal status. The model fits migration rates for illegal immigrants well, but is unable to match the high migration rates and overestimates return migration rates for legal migrants. Legal immigrants are a small part of the sample. The model allows for different moving costs and wages for legal immigrants, but since most of the other parameters are the same, the model cannot fit the data for legal immigrants well.[52] The last four rows split the sample by marital status, first looking at the full history sample and then at the partial history sample. The full history sample is split into married primary movers, married secondary movers, and people who are single. The model underpredicts both the migration rates of married men and women, although it does capture that primary movers are much more likely to move than secondary movers. Table 13 splits the sample by education, looking at the same summary statistics, and again shows that the model is fitting the annual migration rates relatively well. Looking at this along another dimension, Figures 4 and 5 show the annual migration rates over time, and Figures 6 and 7 split the sample by age. The model is fitting the general trends relatively well. However, it is overestimating return migration rates in the later years.

Next I look at the fit of the dynamic aspects of the model. In Table 14, I calculate three statistics in the data: the percent of the sample that moves to the US, the number of moves to the US per migrant, and the average duration of each move to the US. I then simulated

[52]One possible solution would be to allow for a completely different set of parameters for legal immigrants. I chose to not do this due to the computation time to estimate even more parameters. In addition, the counterfactuals focus on illegal immigrants, so it is less important to get a good fit of the data for legal migrants.

the model and calculated the model's predicted values for each of these variables. The model has too few people moving, and those that move stay for longer than in the data. The number of moves per migrant matches the data very well.

Figure 8 shows the model fit for wages of illegal immigrants, splitting the sample by age. For younger ages, the model fits the data well, although it does tend to overestimate wages. For older ages, the model is underestimating wages. The model also estimates wages for legal immigrants. Using the model estimates, I find that the average illegal immigrant would earn 18% more as a legal immigrant. In comparison, Kossoudji and Cobb-Clark (2002) estimate a wage penalty from being an undocumented immigrant of 14–24%. My results fall within their range.

8. Counterfactuals

In the counterfactuals, I study how changes in relative wages and US border enforcement affect immigration decisions. I find that increased Mexican wages reduce migration rates and the duration of stays in the US. Increased border enforcement reduces migration rates and increases return migration rates. However, for married men living in the US alone, there is a secondary effect on return migration, in that it is now harder for their wives to move to the US, providing the men an extra incentive to return home. I isolate this effect in this counterfactual. In all of these counterfactuals, I only include the population of illegal immigrants to focus on the group most affected by policy changes.

In each counterfactual, I simulate the model in the baseline and in the alternate policy environments. I then calculate the percent of the sample that moves to the US, the average number of moves to the US per migrant, the average number of years spent living in the US per move, and the average number of years a person lives in the US over a lifetime. These summary statistics indicate the changes in immigration behavior in these alternate environments.

8.1 Changes in Wages

In the first counterfactual, I look at the effect of a 10% increase in Mexican wages, holding US wages constant.[53] Over time, as Mexico's economy grows, the wage gap between the two countries will decrease. This counterfactual analyzes how this will affect illegal immigration.

[53] This counterfactual is limited because there is no unobserved heterogeneity over Mexican wages in the model.

The first row of Table 15 shows the baseline simulation, and the second row shows the results after a 10% increase in Mexican wages. After this change, fewer people move to the US, and for those that move, the duration of each trip decreases. This reflects a higher value of living in Mexico in the counterfactual due to the higher wages. These effects combine to decrease the average number of years that a person lives in the US by around 5%.

Alternatively, I can use the model to study how migration changes in response to variations in US wages. Lessem and Nakajima (2015) show that downturns in the US economy more adversely affect illegal immigrant wages than native wages, due to the frequent renegotiation of labor contracts in the former population. In the fourth row of Table 15, I show the counterfactual outcomes after a 10% decrease in US wages. This decrease substantially discourages immigration, reducing the number of people who move and the duration of each move. Overall, this decreases the number of years spent in the US by around 13%, a much larger effect than from the 10% increase in Mexican wages. This difference is mostly driven by the fact that a 10% decrease in US wages is larger in magnitude than a 10% increase in Mexican wages due to higher wage levels in the US.

To put these results into perspective, I compare them to the findings in Hanson and Spilimbergo (1999), who find a wage elasticity of migration with response to Mexican wages of between -0.64 and -0.86. My results are not directly comparable, since Hanson and Spilimbergo (1999) are looking at changes in apprehensions, which is a proxy for static migration rates. On the other hand, I calculate how the total number of years a person spends in the US responds to wage changes. Nonetheless, I find an elasticity of -0.54, which is quite close to their range. I can also compare my and their wage elasticity with respect to US wages. Hanson and Spilimbergo (1999) find a wage elasticity of US wages ranging between 0.9 and 1.64. I find an elasticity of 1.17, which falls within that range.

My model allows for internal migration as well as Mexico to US migration, which enables me to study how non-uniform changes in the Mexican economy affect migration patterns. For example, there could be increases or decreases in wages in certain locations in Mexico, and this would not affect everyone directly. However, since people can move internally, changes in wages in alternate Mexican locations could still affect US migration patterns. To put a bound on this, I simulate a version of the model where all wages except those in a person's home location increase by 10%. This change increases the value of living in all Mexican locations except for one's home location, which will increase internal migration. The results are in the third row of Table 15. There is a slight increase in the percent of the sample that moves to the US, which is surprising given that the value of living in Mexico has increased. However, consider the mechanisms in the model.

Due to the increased wages in alternate locations in Mexico, internal migration goes up, which means people are more likely to be living in a non-home location. If starting from a location other than their home location, people are more likely to move to the US, since moving to the US from one's home location means forgoing their home premium. Another reason for this is that increased internal migration rates can cause people to move to locations that have lower costs of moving to the US. The durations of each trip remain the same as in the case of the 10% increase in wages in all Mexican locations. This is an interesting set of results that could not have been discussed without a model that allows for internal as well as international migration.

The results in Table 15 look at the sample as a whole, but I can also use the model to isolate the role that family decisions play. Consider a married man living in the US without his spouse. As Mexican wages increase, his wife will be less likely to join him in the US, providing an extra incentive for him to return home. To isolate this effect, I run a counterfactual where I increase Mexican wages but hold female migration rates at the baseline level. These results (looking at only married men in the full history sample) are in Table 16. The first row shows the baseline case, and the second row shows a counterfactual with a 10% increase in Mexican wages. In the third row, I increase Mexican wages but keep female migration rates at the baseline level. In this case, I see an increase in the number of years a married man spends in the US as compared to the original counterfactual. In the original counterfactual, the increased Mexican wages cause a decrease in migration durations of about 2.74%, as compared to a 1.76% decrease when female migration rates do not adjust.

8.2 Increased Border Enforcement

Next, I calculate how increased enforcement affects immigration, assuming that the number of person-hours allocated to enforcement at each crossing point increases by 50%. This provides insight as to how immigration would respond to further increases in border enforcement.

The results of this counterfactual are in the fifth row of Table 15. The percent of the sample that moves decreases, the number of moves per migrant slightly decreases, and the duration of each move increases, with this last effect reflecting dynamic considerations. Overall, this increase in enforcement reduces the average amount of time a person lives in the US by about 3%.

In the model, individuals not only choose where to live, but also choose where to cross the border when moving to the US illegally. Each crossing point has a different estimated fixed cost and enforcement level. My model can be used to "optimally" allocate border enforcement in the counterfactual. I again assume a 50% total increase in enforcement, where the extra resources are now allocated to minimize illegal immigration rates, assuming that this is the government's objective. The solution to the government's 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 last row of Table 15 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 US decreases by 7%, whereas it decreased by around 3% with the uniform increase in enforcement. This shows that the effect of increased enforcement depends on the allocation of the extra resources.

As with wages, there is a secondary effect on return migration rates for married men. As enforcement increases, durations of stay increase, as discussed above. However, for married men living in the US alone, the increase in migration costs makes it less likely that their wives will join them in the US. This gives an extra incentive for men to return to Mexico, pushing the duration of stays in the US downward. This same mechanism makes married men less likely to move to the US, since the value of living there is now lower because their wives are less likely to move. The composition of the migrant workforce changes in this alternate policy environment. In the baseline case, looking at the full history sample, 17.2% of the person years spent in the US are by married individuals. After the equal costs increase in enforcement, 16.9% of those person years are by married people.

To isolate these mechanisms, in the next counterfactual I increase border enforcement while holding female migration rates constant. Table 16 shows the results of this counterfactual for the sample of married men. The first row shows the baseline case, and the fourth row shows the results for a 50% equal-costs increase in enforcement. The fifth row runs the same counterfactual, holding female migration rates at the baseline level. When the migration rates are held constant, there is an even larger increase in durations for married men as enforcement increases as compared to the original counterfactual scenario.

8.3 Wages and Enforcement

It is interesting to compare the effects of increased enforcement to increased Mexican wages. The 50% increase in enforcement, allocated following the equal-costs strategy, decreases immigration by about 7%. I compare that to the approximate increase in Mexican wages required to reach the same goal. This would occur with close to a 14% increase in Mexican wages, which is a relatively small narrowing of the Mexico-US 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).

Furthermore, changes in enforcement levels can affect the wage elasticity of migration, which is an issue that has been of interest to policymakers. I compare reactions to a 10% increase in Mexican wages. In the baseline case, this results in a 5.4% decrease in years spent in the US. When enforcement is increased by 50% following the equal-costs strategy, a 10% increase in Mexican wages has a larger effect on immigration behavior, reducing the years spent in the US by 6%. This effect is almost completely due to having a larger effect on the number of people who choose to move to the US. After enforcement increases, an increase in Mexican wages has a larger effect on the number of people who move. In both the normal and increased enforcement cases, as Mexican wages increase, durations of each trip to the US decrease, but by similar amounts.

9. Conclusion

In this paper, I estimate a discrete choice dynamic programming model where people pick from a set of locations in the US and Mexico in each period. I allow for a person's decisions to depend on the location of his spouse, where individuals in a household make decisions sequentially. I use this model to understand how wage differentials and US border enforcement affect an individual's immigration decisions.

I allow for differences in the model according to whether a person can immigrate to the US legally. For illegal immigrants, the moving cost depends on US border enforcement. Border enforcement is measured using data from US Customs and Border Protection on the number of person-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 US 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 US over a lifetime by around 5%. Increases in border enforcement would decrease both immigration and return migration, with the latter effect occurring because, as enforcement increases, individuals living in the US expect that it will be harder to re-enter the country in the future. Married men's durations of stay also adjust to changes in their wives' behavior. Because moving to the US is now more costly, women are less likely to join their husbands in the US, providing an extra incentive for the husbands to return home. Overall, a uniform 50% increase in enforcement would reduce the amount of time that individuals in the sample spent in the US by approximately 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 US would drop by about 7%. These results indicate that the effects of enforcement are dependent on the allocation of the extra resources.

These results have important implications. The US government is considering increasing border enforcement in the future. Hanson (2005) reports that expenditures on border enforcement equalled approximately $2.2 billion in 2002. I find that about an extra $1 billion in expenditures would decrease immigration by 7%. 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 US government is to reduce illegal immigration rates, then my model suggests that this has been the correct strategy. Furthermore, if the US increases enforcement in the future, my results indicate that the government 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 US-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.

In this paper, I study immigration in a partial equilibrium framework, not allowing for general equilibrium effects. Increases in immigration could drive down wages in the US or cause higher wages in Mexico. However, there is no clear conclusion with regard to these general equilibrium effects. Kennan (2013) 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 found a small effect of immigration on US wages while other authors have found larger effects.[54] In my model, I also assume that legal immigration status is exogenously determined. In reality, legal immigration rates are determined by how many have applied for visas, which is likely affected by the current number of illegal immigrants (since many people apply for visas after moving to the US). Both of these equilibrium effects pose important questions 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. The paper is also limited in that it does not allow for a relationship between savings and migration decisions, as in Thom (2010) and Adda, Dustmann, and Gorlach (2015). This is an additional area for future research on this topic.

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Tables and Figures

Table 1: Characteristics of full history sample

	Internal Movers	Moves to US	Moves Internally and to the US	Non-Migrant	Legal Immigrant	Whole Sample
Percent Male	60.53%	91.51%	89.51%	50.82%	90.63%	60.66%
Percent Married	67.59%	81.01%	78.40%	75.74%	92.19%	76.24%
Average Age	29.95	30.13	30.74	29.73	30.86	29.88
Years of education						
0-4	16.07%	18.03%	14.81%	17.72%	11.46%	17.33%
5-8	39.47%	43.61%	43.83%	40.48%	53.13%	41.33%
9-11	28.67%	30.34%	26.54%	30.83%	22.92%	30.17%
12	9.42%	5.92%	8.64%	7.66%	8.85%	7.64%
13+	6.37%	2.10%	6.27%	3.30%	3.65%	3.53%
Observations	722	1,048	162	4,333	192	6,457

Notes: Calculated using data from the full history sample in the MMP. For education, the table gives the percent of each group (i.e., internal movers) that has a given level of education.

Table 2: Characteristics of partial history sample

	Moves to US	Non- Migrant	Legal Immigrant	Whole Sample
Percent male	71.85%	43.80%	65.79%	48.94%
Percent married	58.72%	53.40%	70.32%	54.68%
Average age	26.02	24.92	28.21	25.18
0-4 years education	8.96%	9.59%	6.64%	9.42%
5-8 years education	40.05%	29.99%	36.42%	31.80%
9-11 years education	34.07%	31.48%	32.90%	31.94%
12 years education	11.84%	14.39%	15.29%	13.99%
13+ years education	5.09%	14.55%	8.75%	12.85%
Observations	6,742	33,333	994	41,069

Notes: Calculated using data from the partial history sample in the MMP. For education, the table gives the percent of each group (i.e., people that move to the US) that has a given level of education.

Table 3: Family and Migration Rates

	Married men	Single men	Married women (spouse in US)	Single women
0-4 years education	3.44%	4.10%	1.74%	0.81%
5-8 years education	4.92%	4.55%	3.27%	1.43%
9-11 years education	3.82%	3.26%	3.45%	1.30%
12 years education	2.36%	2.60%	6.25%	1.21%
13+ years education	1.14%	1.00%	10.00%	0.58%
Total	4.04	3.74%	3.22%	1.17%

Notes: This table calculates average annual Mexico to US migration rates in the full history sample. For married women, I only include those whose husband is living in the US.

Table 4: Family and Male Return Migration Rates

	Wife in Mexico	Wife in US	Single
0-4 years education	40.55%	15.38%	33.39%
5-8 years education	33.59%	22.22%	31.70%
9-11 years education	39.83%	16.22%	29.43%
12 years education	48.84%	9.09%	26.19%
13+ years education	29.41%	0.00%	35.09%
Total	36.61%	17.88%	30.96%

Notes: This table reports the average annual return migration rates, using the the full history sample.

Table 5: Migration Probit Regression

	Dependent variable = 1 if moves to the US			
	Whole sample	Full history sample	Men	Women
	(1)	(2)	(3)	(4)
5-8 years education	0.00680***	0.00302	0.00242	0.00674**
	(0.000959)	(0.00194)	(0.00260)	(0.00256)
9-11 years education	0.00511***	-0.000856	-0.00347	0.00713**
	(0.00102)	(0.00217)	(0.00289)	(0.00259)
12 years education	-0.00130	-0.00393	-0.00754	0.00714*
	(0.00120)	(0.00326)	(0.00440)	(0.00326)
13+ years education	-0.0191***	-0.0144**	-0.0203***	0.00194
	(0.00147)	(0.00462)	(0.00604)	(0.00538)
Age	-0.00365***	-0.00266*	-0.00319*	-0.0000882
	(0.000521)	(0.00120)	(0.00160)	(0.00122)
Age squared	0.0000408***	0.0000164	0.0000193	-0.0000144
	(0.0000105)	(0.0000231)	(0.0000307)	(0.0000248)
Family in US	0.0104***	0.0161***	0.0206***	0.00427**
	(0.000722)	(0.00149)	(0.00201)	(0.00140)
Legal immigrant	0.0771***	0.0503***	0.0627***	0.0185***
	(0.00356)	(0.00703)	(0.00979)	(0.00393)
Has moved to US before	0.0465***	0.0476***	0.0599***	0.0141***
	(0.00144)	(0.00245)	(0.00321)	(0.00288)
Single man		0.0471***		
		(0.00306)		
Married man		0.0466***	-0.00119	
		(0.00317)	(0.00219)	
Married woman		0.0366***		0.0119***
		(0.00480)		(0.00179)
State fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	421,638	69,344	50,610	16,288

Notes: Standard errors, clustered at the household level, in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Table is reporting marginal effects from a probit regression. The sample includes individuals who were living in Mexico at the start of the period. Column (1) uses the whole sample, and columns (2)–(4) only include the full history sample. For education, the excluded group is people with four or fewer years of education. Married women whose spouse is in Mexico are not included in the regression.

Table 6: Return migration probit regression

Dependent variable=1 if moves from US to Mexico				
	Whole sample	Full history sample	Men	Women
	(1)	(2)	(3)	(4)
5-8 years education	-0.0263***	0.0109	0.00962	0.120
	(0.00699)	(0.0279)	(0.0288)	(0.0983)
9-11 years education	-0.0320***	-0.00796	-0.00648	0.113
	(0.00734)	(0.0308)	(0.0321)	(0.101)
12 years education	-0.0429***	-0.0125	-0.00367	0.00428
	(0.00898)	(0.0434)	(0.0473)	(0.116)
13+ years education	-0.0194	0.0134	0.0515	-0.242
	(0.0109)	(0.0542)	(0.0608)	(0.150)
Age	-0.00495	0.0181	0.0218	0.0410
	(0.00321)	(0.0133)	(0.0138)	(0.0455)
Age squared	0.000104	-0.000237	-0.000293	-0.000844
	(0.0000617)	(0.000248)	(0.000257)	(0.000901)
Family in US	0.0313***	-0.0304	-0.0349	0.0480
	(0.00482)	(0.0208)	(0.0218)	(0.0519)
Legal immigrant	-0.0725***	-0.284***	-0.295***	-0.0167
	(0.00794)	(0.0299)	(0.0311)	(0.0838)
Single man		0.0794*		
		(0.0395)		
Married man, wife in US		-0.0709	-0.149**	
		(0.0631)	(0.0530)	
Married man, wife in Mexico		0.121**	0.0442*	
		(0.0430)	(0.0223)	
Married woman		0.0590		0.0711
		(0.0587)		(0.0552)
State fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	40,268	5,624	5,185	425

Notes: Standard errors, clustered at the household level, in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Table is reporting marginal effects from a probit regression. The sample includes individuals who were living in the US at the start of the period. Column 1 uses the whole sample, and columns (2)–(4) only use the full history sample. The excluded group for education is people with four or fewer years of education.

Table 7: Wage Regressions in Mexico

Dependent variable: Wage in Mexico			
	1989	2004	1989-2004
	(1)	(2)	(3)
Age	2.89***	1.28***	1.38***
	(0.23)	(0.01)	(0.005)
Age-squared	-0.28***	-0.13***	-0.14***
	(0.03)	(0.002)	(0.001)
Male	0.78	0.15***	0.18***
	(0.10)	(0.005)	(0.002)
5-8 years education	1.12***	0.46***	0.72***
	(0.13)	(0.008)	(0.02)
9-11 years education	1.74***	0.95***	1.36***
	(0.14)	(0.008)	(0.01)
12 years education	2.96***	1.26***	2.49***
	(0.15)	(0.01)	(0.02)
13+ years education	5.60***	2.87***	3.99***
	(0.15)	(0.009)	(0.02)
0-4 years education × time			-0.02***
			(0.0004)
5-8 years education × time			-0.02***
			(0.001)
9-11 years education × time			-0.03***
			(0.001)
12 years education × time			-0.09***
			(0.002)
13+ years education × time			-0.78***
			(0.001)
State fixed effects	Yes	Yes	Yes
R-squared	0.19	0.28	0.29

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Age is divided by 10. For education, the excluded group is people with less than five years of education. The dependent variable is hourly wages, in 2000 dollars using PPP exchange rates. Column (3) has data from 1989, 1992, and 1994–2004. Time is (year-1989). Quadratic and cubic terms for time also included in column (3).

Table 8: Utility Parameter Estimates

Wage term	0.056
	(0.0022)
Home bias	0.20
	(0.0040)
With spouse (men)	0.36
	(0.053)
With spouse (women)	0.032
	(0.042)
Family in US	0.029
	(0.012)
Probability (mover type)	0.68
	(0.022)
Log-likelihood	-232,643.05

Notes: Standard errors in parentheses.

Table 9: Immigrant wage estimates

	Illegal	Legal
Age	2.63	6.17
	(1.14)	(0.13)
Age-squared	-0.44	-0.64
	(0.21)	(0.016)
5-8 years education	1.23	1.49
	(0.20)	(0.16)
9-11 years education	1.93	2.80
	(0.21)	(0.16)
12 years education	2.24	4.83
	(0.24)	(0.15)
13+ years education	2.05	6.87
	(0.37)	(0.16)
Family in US	-0.51	
	(0.22)	
Male	1.31	2.76
	(0.28)	(0.047)
Match component	2.29	0.98
	(0.25)	(0.60)
Constant	0.96	-6.96
	(1.44)	(0.27)
Standard deviation of wages	2.52	5.08
	(0.082)	(0.078)
Match probabilities		
Low-low	0.32	
	(2.17)	
Low-medium	0.01	
	(2.01)	
Medium-low	0.01	
	(2.05)	
Medium-medium	0.28	
	(1.96)	

Notes: Standard errors in parentheses. Excluded term from wage equation is people with less than five years of education. Age is divided by 10. The match components are drawn from a three point symmetric distribution around zero, shifting by the estimated value (positive and negative). The first component in the match probability is for the husband, and the second is for the wife. The wage equations also include time trends in education and location fixed effects. These are taken from the raw data in the CPS.

Table 10: Moving Cost Estimates

	Mexico to US	Return Migration	Internal Migration
Fixed cost for men	3.43	3.59	3.53
	(0.47)	(0.37)	(0.12)
Fixed cost for women	2.22	6.40	3.55
	(0.45)	(0.38)	(0.12)
Distance (legal)	0.60	-0.91	0.0000027
	(0.18)	(0.086)	(0.046)
Age	0.0047	0.062	0.13
	(0.013)	(0.014)	(0.0050)
Population size	0.0053	-0.00016	-0.014
	(0.00034)	(0.0013)	(0.00091)
Distance to railroad	0.30		
	(0.027)		
5-8 years education	-0.047		
	(0.089)		
9-11 years education	-0.21		
	(0.084)		
12 years education	0.67		
	(0.12)		
13+ years education	0.98		
	(0.18)		

Notes: Standard errors in parentheses. Distance measured in thousands of miles. Population divided by 100,000.

Table 11: Illegal Immigration Parameter Estimates

Distance	1.23
	(0.056)
Enforcement	0.04
	(0.0069)
Fixed cost	1.17
	(0.39)
Crossing Point Fixed Costs	
El Paso, TX	-1.07
	(0.26)
San Diego, CA	-4.01
	(0.23)
Laredo, TX	-0.37
	(0.28)
Rio Grande Valley, TX	0.065
	(0.30)
Tucson, AZ	-2.05
	(0.24)
El Centro, TX	-2.36
	(0.24)

Notes: Standard errors in parentheses. Enforcement measured in 10,000 person-hours. Distance measured in thousands of miles.

Table 12: Model Fit: Annual Migration Rates

	Mexico to US Migration Rate		Return Migration Rate	
	Model	Data	Model	Data
Whole Sample	2.60 %	2.37%	10.1%	8.50%
Illegal Immigrants	2.53%	2.19%	10.1%	9.31%
Legal Immigrants	16.55%	40.83%	9.78%	4.52%
Full history sample				
Primary Movers	1.45%	3.30%	22.26%	29.03%
Secondary Movers	0.00073%	0.0027%	33.87%	25.48 %
Single People	3.46%	2.15%	10.89%	24.93%
Partial history sample	2.63%	2.46%	9.33%	5.64%

Notes: I calculate the model-predicted Mexico to US and return migration rates for all individuals in the sample, and compare them to rates in the data. For Mexico to US migration, I use all people in Mexico at the start of the period. For return migration, I use all people in the US at the start of the period.

Table 13: Model fit: Annual migration rates

	Mexico to US migration rate		Return migration rate	
Years of education	Model	Data	Model	Data
0-4	2.38%	2.07%	11.55%	11.87%
5-8	2.99%	2.97%	10.42%	8.93%
9-11	3.41%	2.69%	10.65%	8.10%
12	1.81%	1.92%	7.23%	6.0%
13+	0.81%	0.79%	7.96%	7.47%

Notes: I calculate the model-predicted Mexico to US and return migration rates for all individuals in the sample, and compare them to rates in the data. For Mexico to US migration, I use all people in Mexico at the start of the period. For return migration, I use all people in the US at the start of the period.

Table 14: Model Fit: Lifetime Behavior

	Model	Data
Percent that move	17.23%	19.2%
Years per move	5.51	4.39
Number of moves per migrant	1.20	1.18

Notes: These numbers are based on simulations of the model using the data in the sample.

Table 15: Counterfactuals

	Percent that move	Years per move	Moves per mover	Years in US per person
Baseline	17.23%	5.51	1.20	1.14
10% increase in Mexican wages	16.53%	5.43	1.20	1.08
in all locations but home	17.51%	5.44	1.20	1.14
10% decrease in US wages	15.55%	5.29	1.20	0.99
50% increase in enforcement	16.35%	5.67	1.18	1.10
50% increase in enforcement (equal costs)	15.49 %	5.81	1.17	1.05

Notes: These are the results from simulations of the model, only including the sample of individuals who cannot migrate legally.

Table 16: Counterfactuals: Married Men Only

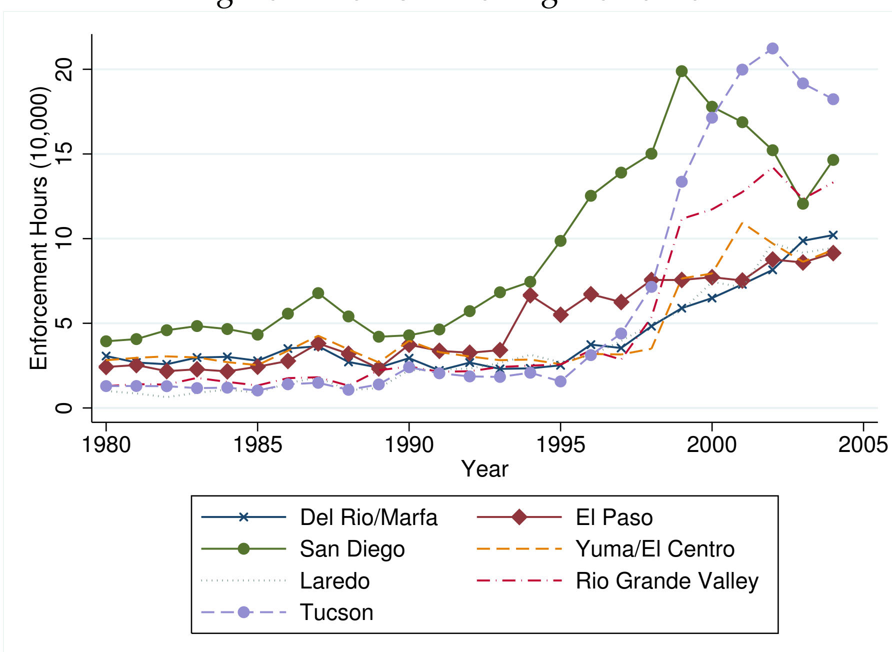
	Percent that move	Years per move	Moves per mover	Years in US per person
Baseline	23.03%	4.85	1.28	1.43
10% increase in Mexican wages	22.11%	4.72	1.28	1.33
Transition probability constant	22.48%	4.77	1.27	1.36
50% equal costs increase in enforcement	20.34%	5.17	1.23	1.30
Transition probability constant	20.67%	5.18	1.23	1.32

Notes: These are the results from simulations of the model, only including the sample of married men who cannot migrate legally.

Figure 1: Border Patrol Sectors

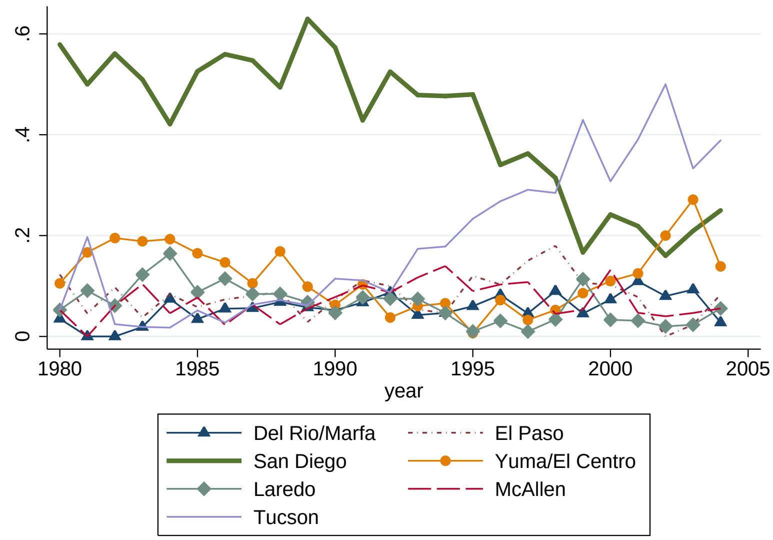
Notes: Map downloaded from US CBP website.

Figure 2: Hours Patrolling the Border



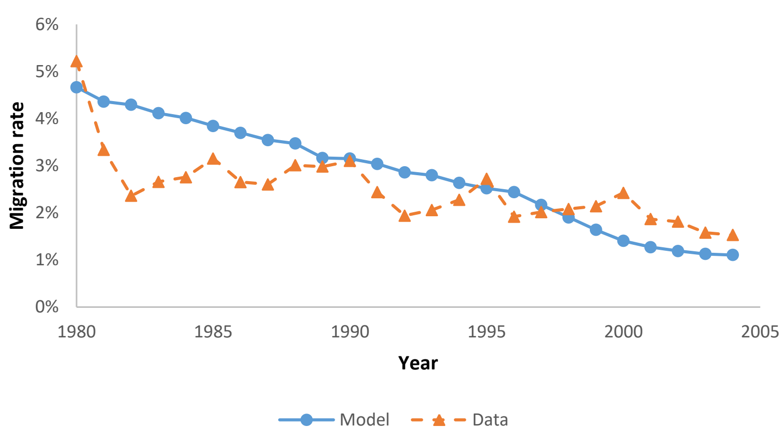
Notes: Data on enforcement from US CBP.

Figure 3: Border Crossing Locations (MMP)



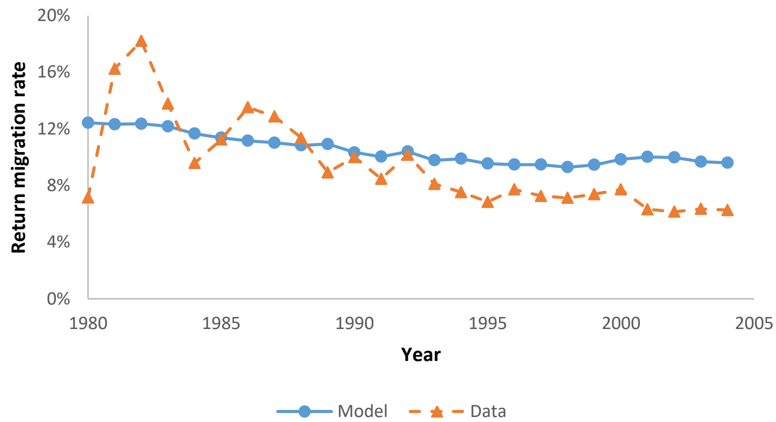
Notes: In this figure, I use data from the MMP to calculate the share of illegal migrants that cross at each border patrol sector in each year.

Figure 4: Model Fit: Mexico to US Migration Rates by Year



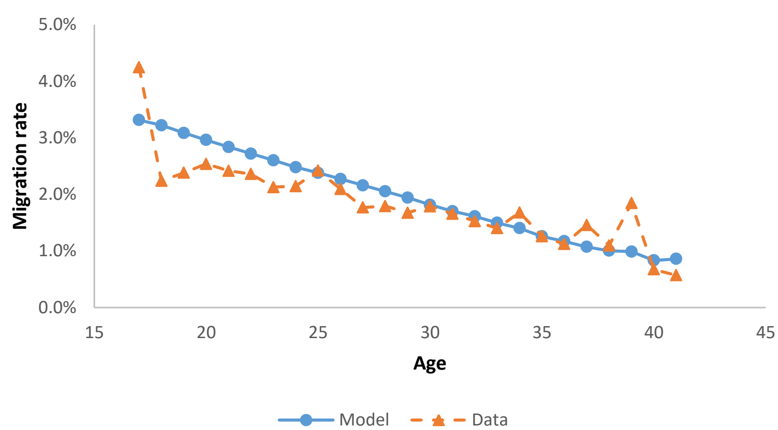
Notes: For each year, I calculate the average Mexico to US migration rate, in the data and as predicted by the model.

Figure 5: Model Fit: Return Migration Rates by Year



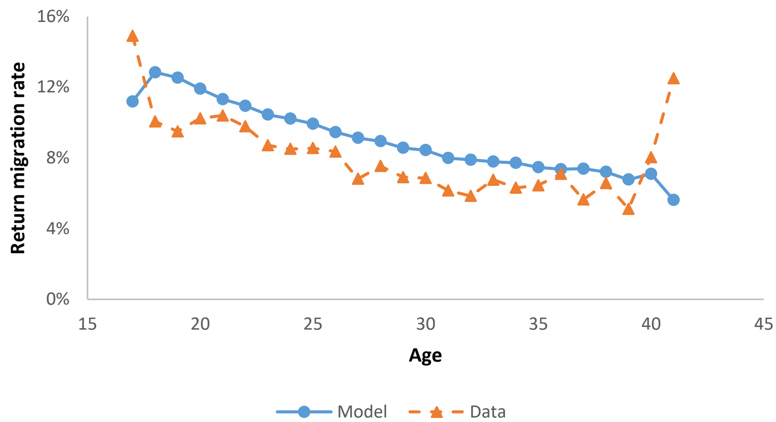
Notes: For each year, I calculate the average return migration rate, in the data and as predicted by the model.

Figure 6: Model Fit: Mexico to US Migration Rates by Age



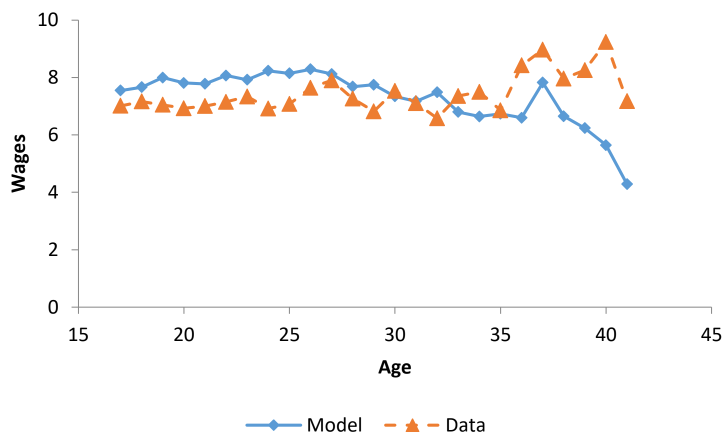
Notes: For each age, I calculate the average Mexico to US migration rate, in the data and as predicted by the model.

Figure 7: Model Fit: Return Migration Rates by Age



Notes: For each age, I calculate the average return migration rate, in the data and as predicted by the model.

Figure 8: Model Fit: Wages for Illegal Immigrants



Notes: I calculate the average wage of people living in the US illegally, in the data and as predicted by the model.

Appendix A (for online publication)

Table A1: Comparison of MMP sample and CPS sample

	MMP sample	MMP sample (legal)	CPS
Percent male	74.84%	74.22%	51.01%
Average age	24.51	27.51	34.55
0-4 years education	9.24%	6.28%	11.51%
5-8 years education	42.91%	43.05%	25.10%
9-11 years education	33.89%	31.84%	19.80%
12 years education	9.24%	12.33%	27.75%
13+ years education	4.73%	6.50%	15.84%
Observations	2,349	446	135,776

Notes: For education, the table gives the percent of each sample that has a given level of education. This uses data from 1980–2004 in the MMP and CPS, where in the former I use observations when a person is living in the US and in the latter I use data on individuals born in Mexico (or of Hispanic ethnicity when country of birth is not available).

Table A2: Comparison of MMP sample and the 2000 Mexico census

	MMP sample	Mexico census
Percent male	47.29%	47.88%
Average age	19.98	34.45
0-4 years education	5.80%	28.96%
5-8 years education	25.05%	28.45%
9-11 years education	39.17%	22.91%
12 years education	16.92%	9.20%
13+ years education	13.06%	10.48%
Observations	1034	5,347,214

Notes: For education, the table gives the percent of each sample that has a given level of education. This uses data from 2000 in the MMP and the Mexican census, where in the former I only use data on people living in Mexico in 2000 and the latter uses the population aged 17–65 in the census.

Table A3: Sample sizes in each state

State	Sample size	Combined with
Aguascalientes	6,329	Nayarit
Baja California del Norte	9,793	Baja California del Sur
Baja California del Sur	95	Baja California del Norte
Campeche	65	Chiapas, Quintana Roo, and Yucatan
Coahuila	412	Morelos and Tamaulipas
Colima	6,400	
Chiapas	232	Campeche, Quintana Roo, and Yucatan
Chihuahua	25,153	Sonora
Distrito Federal	8,438	
Durango	13,936	
Guanajuato	36,801	
Guerrero	7,045	
Hidalgo	7,589	
Jalisco	59,173	
Mexico	19,671	
Michoacan	18,667	
Morelos	16,282	Coahuila and Tamaulipas
Nayarit	2,848	Aguascalientes
Nuevo Leon	10,303	
Oaxaca	8,115	
Puebla	21,136	
Queretaro	16,524	
Quintana Roo	499	Campeche, Chiapas, and Yucatan
San Luis Potosi	25,417	
Sinaloa	9,090	
Sonora	462	Chihuahua
Tabasco	12,270	
Tamaulipas	1,008	Coahuila and Morelos
Tlaxcala	10,200	
Veracruz	32,458	
Yucatan	13,758	Campeche, Chiapas,and Quintana Roo
Zacatecas	13,049	

Notes: Table gives the number of person-year observations in each state in the MMP, and lists which states were combined in the estimation.

Table A4: Wage Regressions in Mexico (1989, 1992, 1994)

	Dependent variable: wage in Mexico		
	1989	1992	1994
	(1)	(2)	(3)
Age	2.90***	2.42***	1.92***
	(0.23)	(0.26)	(0.19)
Age-squared	-0.28***	-0.23***	-0.15***
	(0.03)	(0.03)	(0.03)
Male	0.78***	0.57***	0.40***
	(0.10)	(0.11)	(0.09)
5-8 years education	1.12***	0.98***	0.91***
	(0.13)	(0.14)	(0.11)
9-11 years education	1.74***	1.76***	1.60***
	(0.14)	(0.15)	(0.12)
12 years education	2.96***	2.93***	3.23***
	(0.15)	(0.17)	(0.13)
13+ years education	5.60***	6.41***	7.61***
	(0.15)	(0.17)	(0.13)
Constant	-4.32***	-4.02***	-3.48***
	(0.46)	(0.52)	(0.40)
State fixed effects	Yes	Yes	Yes
Observations	11,274	9,929	12,452
R-squared	0.19	0.18	0.29

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Age is divided by 10. For education, the excluded group is people with less than five years of education. The dependent variable is hourly wages, in 2000 dollars adjusted using PPP exchange rates. Data from the ENIGH.

Table A5: Wage Regressions in Mexico (1995–1999)

	Dependent variable: wage in Mexico				
	1995	1996	1997	1998	1999
	(1)	(2)	(3)	(4)	(5)
Age	1.58***	1.31***	1.41***	1.35***	1.21***
	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)
Age-squared	-0.16***	-0.13***	-0.14***	-0.13***	-0.12***
	(0.006)	(0.003)	(0.005)	(0.003)	(0.004)
Male	0.02	0.008	0.02	0.08***	0.08***
	(0.02)	(0.008)	(0.02)	(0.008)	(0.01)
5-8 years education	0.49***	0.46***	0.45***	0.46***	0.42***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
9-11 years education	1.14***	1.03***	1.08***	1.07***	0.98***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
12 years education	1.57***	1.35***	1.53***	1.40***	1.25***
	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)
13+ years education	3.28***	2.84***	3.03***	2.93***	2.84***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)
Constant	-1.97***	-1.62***	-1.91***	-1.66	-1.43
	(0.11)	(0.04)	(0.08)	(0.06)	
State fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	43,177	139,806	48,744	153,381	66,045
R-squared	0.30	0.31	0.32	0.31	0.32

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Age is divided by 10. For education, the excluded group is people with less than five years of education. The dependent variable is hourly wages, in 2000 dollars adjusted using PPP exchange rates. Data from the ENE.

Table A6: Wage Regressions in Mexico (2000–2004)

	Dependent variable: wage in Mexico				
	2000	2001	2002	2003	2004
	(1)	(2)	(3)	(4)	(5)
Age	1.45***	1.43***	1.39***	1.34***	1.29***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age-squared	-0.15***	-0.14***	-0.14***	-0.13***	-0.13***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Male	0.18***	0.21***	0.22***	0.19***	0.15***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
5-8 years education	0.52***	0.53***	0.51***	0.48***	0.46***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
9-11 years education	1.11***	1.11***	1.08***	1.02***	0.95***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
12 years education	1.47***	1.46***	1.41***	1.34***	1.26***
	(0.01)	(0.01)	(0.009)	(0.01)	(0.01)
13+ years education	3.19***	3.17***	3.16***	3.08***	2.87***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)
Constant	-1.82***	-1.74***	-1.63***	-1.53***	-1.37***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	563,799	752,772	727,185	634,792	478,129
R-squared	0.31	0.30	0.30	0.29	0.28

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Age is divided by 10. For education, the excluded group is people with less than five years of education. The dependent variable is hourly wages, in 2000 dollars adjusted using PPP exchange rates. Data from the ENE.

Table A7: Transition Rates in Model

	Legal status	Married
	(1)	(2)
5-8 years education	0.000888***	0.00247
	(0.000264)	(0.00183)
9-11 years education	0.000670*	-0.00119
	(0.000270)	(0.00193)
12 years education	0.000601	-0.00746ym**
	(0.000309)	(0.00284)
13+ years education	-0.000987**	-0.00942*
	(0.000364)	(0.00366)
Age	0.000495**	-0.000366
	(0.000151)	(0.00204)
Age squared	-0.0000105***	-0.0000927*
	(0.00000294)	(0.0000437)
Family in US	0.00205***	-0.000957
	(0.000164) (0.00174)	
Male	0.00189***	0.0187***
	(0.000165)	(0.00169)
In US		0.000625
		(0.00234)

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Table is reporting marginal effects from the probit regression on whether (1) people get legal status in each year, and (2) whether they get married each year. In column (1), the sample includes respondents that did not have ability to move legally in the previous period. In column (2), the sample includes people who were single in the previous period.

Appendix B (for online publication)

In this Appendix, I outline identification of the key moving cost parameters related to illegal immigration.

To do this, I consider a two-location static model to highlight the key mechanisms. Assume wages in the two locations are given by w_t^{US} and w_t^{MEX}, in the US and Mexico, respectively, and denote the effect of wages on utility as α. I simplify utility so that it only depends on wages. If a person moves to the US, assume he has two crossing point options. The cost of crossing at point 1 is given by $c^1 - \lambda b_t^1$, and the cost of crossing at point 2 is given by $c_2 - \lambda b_t^2$. In this case, c^1 and c^2 are the fixed costs of crossing at each point, b_t^1 and b_t^2 are the border enforcement levels at each point at time t, and λ is the effect of border enforcement on moving costs.

Consider migration rates at time t. The probability that a person crosses the border through crossing point one and two is given by:

$$p_t^1 = \frac{\exp(\alpha w_t^{US} - c_1 - \lambda b_t^1)}{\exp(\alpha w_t^{MEX}) + \exp(\alpha w_t^{US} - c_1 - \lambda b_t^1) + \exp(\alpha w_t^{US} - c_2 - \lambda b_t^2)} \tag{18}$$

$$p_t^2 = \frac{\exp(\alpha w_t^{US} - c_2 - \lambda b_t^2)}{\exp(\alpha w_t^{MEX}) + \exp(\alpha w_t^{US} - c_1 - \lambda b_t^1) + \exp(\alpha w_t^{US} - c_2 - \lambda b_t^2)} \tag{19}$$

Taking the ratio of these two probabilities, I get

$$\frac{p_t^1}{p_t^2} = \exp(-c_1 - \lambda b_t^1 + c_2 + \lambda b_t^2). \tag{20}$$

Taking the log of both sides results in the following expression:

$$\log\left(\frac{p_t^1}{p_t^2}\right) = c_2 - c_1 - \lambda(b_t^2 - b_t^1). \tag{21}$$

Equation (21) has three unknowns. I can take the same ratio at time t' to get a second equation:

$$\log\left(\frac{p_{t'}^1}{p_{t'}^2}\right) = c_2 - c_1 - \lambda(b_{t'}^2 - b_{t'}^1). \tag{22}$$

I now have two equations and three unknowns. The necessary condition for identification is that border enforcement at crossing point one and crossing point two grow at different speeds, which is consistent with the data. I normalize the cost of crossing at point one to zero, meaning the fixed cost at point two will be defined relative to the fixed cost at point one. The result is a system of two linear equations and two variables, providing identification of the fixed costs of crossing and the effect of border enforcement. In the more general case with seven crossing points, I set the fixed cost of crossing at the first one to zero, and then can identify the rest of the fixed costs. The intuition behind this argument comes from comparing the migration rates through each border crossing point over time. As enforcement at crossing point one increases, a greater ratio of the migrants will shift to crossing at point two. To see the identification of the fixed costs of crossing, consider the case where border enforcement is equal at sector one and two. In this case, the fixed cost is identified based on how many people cross at sector two relative to sector one.

Appendix C (for online publication)

In this appendix, I discuss the parameterization of the moving cost function and the utility function.

Moving cost function

Recall from Section 3.2 that $c_t(\cdot)$ is the moving cost function. This function depends on a person's legal status, characteristics, and on which locations he is moving between:

$$c_t(\ell_1, \ell_2, X_t, z_t) = \begin{cases} c_t^1(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_M, \ell_2 \in J_U, z_t = 1 \\ c_t^2(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_M, \ell_2 \in J_U \times C, z_t = 2 \\ c_t^3(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_U, \ell_2 \in J_M \\ c_t^4(\ell_1, \ell_2, X_t) & \text{if } \ell_1 \in J_M, \ell_2 \in J_M \,. \end{cases} \tag{23}$$

The moving cost is given by $c_t^1(\cdot)$ for legal immigrants moving to the US, $c_t^2(\cdot)$ for illegal immigrants moving to the US, $c_t^3(\cdot)$ 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 US and a border crossing point, as the moving cost for illegal immigrants depends on both of these factors. I define each of the moving cost functions as follows:

$$\begin{aligned} c_t^1(\ell_1, \ell_2, X_t) &= \lambda_1 + \lambda_2 d(\ell_1, \ell_2) + \lambda_3 rr(\ell_1) + \lambda_4 age + \lambda_5 pop(\ell_2) \\ &+ \sum_{q=1}^{N_e} \lambda_q^e educ_q \end{aligned} \tag{24}$$

$$\begin{aligned} c_t^2(\ell_1, \ell_2, X_t) &= \lambda_1 + \lambda_2 d(\ell_1, \ell_2) + \lambda_3 rr(\ell_1) + \lambda_4 age + \lambda_5 pop(\ell_2) \\ &+ \sum_{q=1}^{N_e} \lambda_q^e educ_q + \lambda_6 + \lambda_7 \tilde{b}_{kt} + \lambda_k^b \end{aligned} \tag{25}$$

$$c_t^3(\ell_1, \ell_2, X_t) = \lambda_8 + \lambda_9 d(\ell_1, \ell_2) + \lambda_{10} age + \lambda_{11} pop(\ell_2) \tag{26}$$

$$c_t^4(\ell_1, \ell_2, X_t) = \lambda_{12} + \lambda_{13} d(\ell_1, \ell_2) + \lambda_{14} age + \lambda_{15} pop(\ell_2) \,. \tag{27}$$

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 US (λ_1), back to Mexico (λ_8), or within Mexico (λ_{12}). If a person is moving to the US illegally, I allow for an increase in the fixed cost (λ_6). If moving to the US, the distance from a location to the railroad (denoted as $rr(\ell_1)$) affects the moving cost. The cost of moving also depends on age, which affects moving costs linearly. The population size of the destination also affects moving costs. For people moving to the US, I allow the moving cost to depend on education. I estimate an extra fixed cost for each education level. The term λ^e_q is the estimated fixed cost for education group q, and there are N_e education groups. The term $educ_q$ is a dummy variable that equals 1 if a person is in education group q.[55]

US border enforcement affects the border crossing costs for illegal immigrants. However, there is potential endogeneity in that enforcement at each sector could be affected by the number of migrants crossing there. To account for this, I follow Bohn and Pugatch (2015) and use the enforcement levels, lagged by 2 periods, to predict future enforcement. Budget allocations for border enforcement are typically determined two years ahead of time, although extra resources can be allocated when needed due to unexpected shocks. The two-year-lagged values of border enforcement levels represent the best predictor of future enforcement needs before these shocks hit. This controls for endogeneity of enforcement and migration flows at each sector. The term $\tilde{b}_{kt}$ in the moving cost function is the predicted level of border enforcement at crossing point k at time t, and λ_7 is the effect of border enforcement on the moving cost.

Each border crossing point has its own fixed cost, denoted as λ^b_k.[56] 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.

Utility function

The utility function depends on a person's location, characteristics, legal status, and the location of a person's spouse. In particular, I assume that utility increases if he is in the same country as his spouse, instead of keeping track of his spouse's exact location.

I write the utility function as

$$u(\ell_t, X_t, z_t, m_t, \ell^s_t) = \begin{cases} \alpha_w E w_t(X_t, \ell_t, z_t) + \alpha_H \mathbb{1}(\ell_t = H) + \alpha_S & \text{if } \ell_t \in J_M \text{ , } \ell^s_t \in J_M \\ \alpha_w E w_t(X_t, \ell_t, z_t) + \alpha_H \mathbb{1}(\ell_t = H) + \alpha_S + \alpha_F f & \text{if } \ell_t \in J_U \text{ , } \ell^s_t \in J_U \\ \alpha_w E w_t(X_t, \ell_t, z_t) + \alpha_H \mathbb{1}(\ell_t = H) + \alpha_F f & \text{if } \ell_t \in J_U \text{ , } \ell^s_t \in J_M \\ \alpha_w E w_t(X_t, \ell_t, z_t) + \alpha_H \mathbb{1}(\ell_t = H) & \text{if } \ell_t \in J_M \text{ , } \ell^s_t \in J_U \text{ .} \end{cases} \tag{28}$$

Utility depends on a person's expected wage, where each \$1 increase in expected wage increases utility by α_w. In the utility function, $\mathbb{1}(\cdot)$ is an indicator function that equals

[55] 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.

[56] There are seven crossing points, and I estimate six fixed costs. The seventh is set to zero and the other fixed costs represent the change in fixed cost between that point and the baseline crossing point.

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 H, which is defined as the state in which he was born. For married individuals, utility increases by α_S if both spouses are in the same country. I allow this parameter to vary with gender. This accounts for the fact that this premium could be more important for one gender than the other. In addition, I allow for higher utility in the US if a person also has family members living there. The dummy variable f equals 1 if a person has family in the US, and utility increases by α_f in this case.

Appendix D (for online publication)

In this appendix, I explain how the likelihood function is calculated. I calculate the likelihood for each household, integrating over the probability that each household has a specific moving cost type, the probability that each person has a specific wage fixed effect, and the probability that the woman is a worker type.

Denote the set of utility and moving cost parameters to be estimated as θ_τ for a household with moving cost type τ. For each household h, I observe a history of location choices for the primary and secondary mover $\mathbb{L}_h = (\mathbb{L}_h^1, \mathbb{L}_h^2) = (\{\ell_{h0}^1, \ell_{h1}^1, ..., \ell_{hT}^1\}, \{\ell_{h0}^2, \ell_{h1}^2, ..., \ell_{hT}^2\})$. The first location ($\ell_{h0}$), a person's location at age 17, is taken as exogenous. The remainder 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.[57]

For each person, I also observe wage draws when in the US. For each household, denote the set of wage draws in the US as W_h. Denote the set of wage heterogeneity terms for each individual in the household as κ, where $\kappa = (\kappa^1, \kappa^2)$. Again, these are individual specific terms, known by every member of the household and unobserved by the econometrician. There are three possible values for κ_1 and κ_2. I estimate the probability that a husband and wife have each type, allowing for a correlation between the types of spouses.

First I explain how I calculate the likelihood function for the full history sample. I start by solving for this conditional on moving cost type and wage type. The first component is the choice probabilities $P^1(\cdot)$ and $P^2(\cdot)$, as defined in equations (11) and (6). A woman can either work or not work.[58] The other component of the likelihood is the wage density $f_w(\cdot)$.[59] The probability of seeing an observed history for household h, conditional on unobserved types over moving costs and wages, is written as

$$\begin{aligned}\chi^0(\mathbb{L}_h, W_h|\kappa, \theta_\tau) \quad = \quad & \prod_{t=1}^{T} \Big[P_t^1(\ell_{ht}^1|\ell_{h,t-1}^1, \Delta_{ht}^1, m_{ht}^1, \ell_{h,t-1}^2, \kappa, \theta_\tau) f_w(w_{ht}^1|z_{ht}^1, X_{ht}^1, \ell_{ht}^1, \kappa^1) \\ \times \quad & P_t^2(\ell_{ht}^2|\ell_{h,t-1}^2, \Delta_{ht}^2, m_{ht}^2, \ell_{ht}^1, \kappa, \theta_\tau) f_w(w_{ht}^2|z_{ht}^2, X_{ht}^2, \ell_{ht}^2, \kappa^2) \Big]. \qquad (29)\end{aligned}$$

[57] Many households start as unmarried but become married in a future period. In the estimation, I calculate the likelihood at the household level, where people make decisions as single agents before they are married, and then their decisions relate to one another once married.

[58] If the woman is a non-worker type, I set $\alpha_w = 0$ to indicate that her utility is not affected by wages.

[59] I define $f_w(\cdot) = 1$ when a person is living in Mexico, and I cannot calculate the likelihood of a wage offer.

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, where it is important to remember that a choice today becomes part of the state space tomorrow. In addition, when a person is living in the US, his wage draw enters the likelihood function.

Equation (29) is conditional on the wage-types of the husband and wife. I allow for a correlation between the types of husbands and wives. In particular, I estimate a set of parameters $\{\nu_\kappa\}$, where the ν terms include the probability that the wife is a worker type,[60] and the correlations between the types of husbands and wives. This allows for assortative matching in the labor market, if the estimates reveal that a high-wage type man is most likely to be married to a high-wage type woman. The parameters are fixed so that the total probability that a man or a woman is each type is set at 1/3.

I integrate over the worker type probabilities as follows:

$$\chi(\mathbb{L}_h, W_h|\theta_\tau) = \sum_\kappa \nu_\kappa \chi^0(\mathbb{L}_h, W_h|\kappa, \theta_\tau) \, . \tag{30}$$

To calculate the full likelihood, I still need to integrate over moving cost type. I denote p_τ as the probability that a household has moving cost type τ. Denote the set of households in the full history sample as N_{FH}.

$$L^{FH}(\theta) = \sum_{h \in N_{FH}} \log\left(\sum_\tau p_\tau \chi(\mathbb{L}_h, W_h|\theta_\tau)\right) \, . \tag{31}$$

For the partial history sample, I do not see their full history of migration decisions, and therefore have to integrate out their decisions over years where I do not know where they are. This makes computation of the likelihood function more complicated. For this group, everyone is treated as a single person because I do not know marital status at each point in time.

For every person and year where I do not see his observed location choice, I calculate the probability (as given by the model) that he is in each location in the missing years. For example, take a person who is at location ℓ_1 in period one, and then I do not see his location again until time five, when he is at location ℓ_5. I first calculate the likelihood he is at location ℓ_5 conditional on all possible locations for time 4. Then, I need the probability he is at each of these locations in period 4. This comes from the model, where starting with the known location ℓ_1, I can calculate the probability that he ends up in each location in period four. Then, at period 5, I know he chooses location ℓ_5. I can calculate the

[60] This value is fixed using data from the World Development Indicators.

probability that he chooses that location at that time period conditional on each possible prior location. Multiplying that value times the probability that he is in each location, and then summing over all possible locations, gives the likelihood for that time period. I use this strategy to calculate the likelihood function for the partial history sample.

Denote $\mathbb{L}_i$ as the set of location choices that are observed for a person who is in the partial history sample, and denote $\tilde{\ell}_{it}$ as his last known location as of time t, realized at time s. If $s = t$, this means there are no gaps. I define the functions $g_t^1(j|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau)$ and $g_t^2(j|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau)$ as the probability that a person is in location j at time t, conditional on his previous known location and unobserved type. The superscripts one and two are for primary and secondary movers, respectively.[61] These functions are defined as follows:

$$g_t^1(j|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau) = \begin{cases} \sum_k P_t^1(j|k, X_{it}, \kappa, \theta_\tau) g_{t-1}^1(k|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau) & \text{if } s \neq t \\ 1 & \text{otherwise} \end{cases} \tag{32}$$

$$g_t^2(j|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau) = \begin{cases} \sum_k P_t^2(j|k, X_{it}, \kappa, \theta_\tau) g_{t-1}^2(k|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau) & \text{if } s \neq t \\ 1 & \text{otherwise} \end{cases} \tag{33}$$

By starting with the first period with an unknown location, I can iterate on the g function and solve for the probability that a person is in each location at the start of future periods. In particular, in the first period where I know the person's location but not his immediately previous-period location, I use equations (32) and (33) to solve for the probability that he is in each location in the prior period. I then multiply the probability that he makes the observed location choice, conditional on being in a given previous-period location, by the probability of having that previous-period location. I sum over previous-period locations to get the likelihood.

Conditional on moving cost and wage type, the likelihood for a primary and secondary mover is as follows:

$$\begin{aligned} \Psi^1(\mathbb{L}_i|X_i, \kappa, \theta_\tau) &= \prod_{t=1}^{T} \sum_{\ell_{i,t-1}} P_1^t(\ell_{it}|\ell_{i,t-1}, X_{it}, \kappa, \theta_\tau) g^1(\ell_{i,t-1}|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau) \\ &\times f_w(w_{it}|z_{it}, X_{it}, \ell_{it}, \kappa) \end{aligned} \tag{34}$$

$$\begin{aligned} \Psi^2(\mathbb{L}_i|X_i, \kappa, \theta_\tau) &= \prod_{t=1}^{T} \sum_{\ell_{i,t-1}} P_2^t(\ell_{it}|\ell_{i,t-1}, X_{it}, \kappa, \theta_\tau) g^2(\ell_{i,t-1}|\tilde{\ell}_{it}, X_{it}, \kappa, \theta_\tau) \\ &\times f_w(w_{it}|z_{it}, X_{it}, \ell_{it}, \kappa). \end{aligned} \tag{35}$$

I can use this to calculate the likelihood function for the partial history sample. Denote $N_{PH,M}$ as the sample of men in the partial history sample, and denote $N_{PH,F}$ as the sample

[61] Everyone is treated as single, but I use the primary and secondary mover notation to differentiate between the decisions of men and women.

of women in the partial history sample. Each person has probability p_τ of having each moving cost type and probability $1/3$ of having each wage type. Then the likelihood for the partial history sample is

$$\begin{aligned} L^{PH}(\theta) &= \sum_{i \in N_{PH,M}} \log \left(\sum_{\tau} \sum_{\kappa} \frac{p_\tau \Psi^1(\mathbb{L}_i | X_i, \kappa, \theta_\tau)}{3} \right) \\ &+ \sum_{i \in N_{PH,F}} \log \left(\sum_{\tau} \sum_{\kappa} \frac{p_\tau \Psi^2(\mathbb{L}_i | X_i, \kappa, \theta_\tau)}{3} \right) \end{aligned} \tag{36}$$

The last component of the likelihood function is the wage component from the CPS, used to help identify the wage parameters for legal immigrants. I use wages (for Mexican-born individuals) from the CPS as extra data to more precisely estimate these parameters since the sample of legal immigrants in the MMP is small.[62][63] For these individuals, I do not know their migration histories, and only know their wage outcomes in the US. Denote N_{CPS} as the set of individuals in the CPS sample. They contribute to the likelihood through their wage outcomes. Their contribution to the likelihood is as follows:

$$L^{CPS}(\theta) = \sum_{i \in N_{CPS}} \log \left(\sum_{\kappa} \frac{f_w(w_{it} | z_{it} = 1, X_{it}, \ell_{it}, \kappa)}{3} \right) . \tag{37}$$

The log-likelihood function is the sum of the partial history, full history, and CPS likelihoods:

$$L(\theta) = L^{FH}(\theta) + L^{PH}(\theta) + L^{CPS}(\theta) . \tag{38}$$

[62] I use Hispanic ethnicity when country of birth is not available.

[63] These estimates likely cause an upward bias because I cannot model their migration decisions and therefore cannot control for selection into migration. The CPS data is only used to pin down the parameters of the legal migrant wage distribution, so any bias is limited to these parameters.

Appendix E (for online publication)

The model is estimated using Fortran on a server with approximately 40 cores. The use of multiple cores allows me to substantially decrease computation time. I split the state space into different groups, and calculate the value functions for each group on a different core. I then can calculate the value of the likelihood for the full sample for a given set of parameters. I maximize the likelihood function using the dfpmin algorithm. This procedure uses the Davidon-Fletcher-Powell Method, which is a quasi-Newton method.

One concern is that the routine could find local optima instead of the global optimum. To account for this, I estimated the model many times, each time randomly selecting initial guesses for the parameters. In most cases, the estimation converged to the same point.