Repeated Circular Migration: Theory and Evidence from Undocumented Migrants

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Abstract

This paper contributes to the literature on temporary migration by developing a model of repeated circular migration that accounts for saving behavior. Using Mexican Migrant Project data on undocumented migrants and non-migrants, I estimate the parameters of the model through the Method of Simulated Moments. The intensity of U.S. border enforcement is found to have a significant positive effect on the cost of migration for at least one group of individuals. Counterfactual experiments suggest that an increase in the intensity of border enforcement over the sample period would have reduced migration rates in the sample, but would have increased trip durations. I do not find evidence for the hypothesis that tougher border enforcement increases the population of undocumented migrants by trapping them in the United States. Counterfactual simulations suggest that continual increases in border enforcement will not produce continual reductions in migration rates because some individuals are immune to the effects of such policy changes. Migration behavior is also found to be sensitive to changes in the exchange rate, which alter both the cost of migration and the value of foreign earnings.

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1 Introduction

Undocumented immigration has emerged as a perennial source of controversy in American political and economic discourse. While many questions related to the economic costs and benefits of undocumented immigration remain disputed, the steady growth of the population of undocumented immigrants in the United States appears beyond doubt. Researchers employing a variety of techniques have consistently found significant growth in the population of undocumented immigrants in the United States over the last twenty years.[1] For example, INS data collected over the years 1990-2000 suggest that in the span of a decade, the undocumented population has doubled, growing from 3.5 million to 7 million persons. (Hanson, 2006)

Mexico is by far the most significant source country for undocumented immigrants in the United States. Passel (2005) estimates that Mexicans accounted for about 57% of the population of undocumented immigrants in 2004. Historically, undocumented migration between Mexico and the United States has been distinguished by its circularity. As Massey et al. (2003) describe, undocumented Mexican migrants often reside and work in the United States temporarily, remitting money home or accumulating savings before returning to Mexico. Moreover, undocumented Mexican migrants tend to engage in repeated circular migration, moving back and forth between Mexico and the United States several times over the course of their lives. (Massey and Espinosa, 1997)

Identifying the factors that drive repeated circular migration is therefore necessary for understanding the phenomenon of undocumented Mexican migration and analyzing related policy issues, such as the effect of U.S. border enforcement strategy. A number of studies have explored how the duration and frequency of migratory trips vary with individual characteristics and policy variables. However, since this literature typically uses reduced form methods, it reaches few conclusions about the underlying incentives and behavioral parameters that govern migration. Yet, it is precisely these structural parameters that determine how migration behavior will change as important economic or policy variables change.

This paper develops a dynamic model of circular migration that explains the behavior of migrants as a function of the international wage gap, the exchange rate, a preference for residence in the home country, and the cost of migration. The model allows individuals to accumulate assets and move back and forth repeatedly between the home and foreign countries. These two behaviors are common among undocumented Mexican migrants, but are rarely combined in the literature. I estimate the model using Mexican Migrant Project (MMP) data on several cohorts of young men during the period 1987-2000.

[1] See Hanson (2006) for a survey of recent work on this topic.

This paper makes several contributions to the literature on circular migration, and in particular the structural literature on Mexican migration (Colussi, 2006; Rendon and Cuecuecha, 2007). The empirical results provide the first structural estimates of the effects of changes in U.S. border enforcement and real exchange rates on Mexican migration. In both cases, countervailing incentives make the directions of these relationships ambiguous. The empirical model is able to answer these questions because it explicitly accounts for key trends and structural breaks in the processes that govern income, the real exchange rate, and the intensity of border enforcement. Controlling for these features not only permits unique empirical results, but it is also important for the credibility of parameter estimates. Mexican migration data from the 1990s do not reflect choices made in response to a stationary environment, but rather behavior in the face of a series of macro developments, including the Peso Crisis, which unleashed a 30% decline in real wages in Mexico, a 50% spike in the real exchange rate, and a massive escalation in border enforcement. The estimation procedure here also employs a new weighting scheme for the MMP data that addresses concerns about the over-representation of high-migration regions, and the under-representation of long-term migrants.

The key findings include the following: (1) More aggressive border enforcement policies significantly increase the cost of migration for most individuals, reducing migration rates and causing migrants to take fewer but longer trips. (2) One of the criticisms of tough border enforcement strategies is that they might backfire and cause individuals to spend more time in the United States as they forgo return trips to Mexico. Counterfactual policy experiments suggest that higher levels of the intensity of U.S. Border Patrol activity would not have increased the total amount of time that the average individual in the sample spent in the Unites States. If the United States had not increased border enforcement in response to the Peso Crisis, time spent in the United States would have increased by 20% (3) The net effect of an increases in the exchange rate (pesos per dollar) is to reduce migration rates and trip durations. This is the result of offsetting effects on the cost of migration and the value of foreign earnings.

The paper proceeds as follows. Section 2 provides a review of the literature related to temporary Mexican migration and models of circular migration. Section 3 develops a structural model of repeated circular migration. Section 4 describes the MMP data and characterizes the pattern of migration in our sample. Section 5 outlines the estimation strategy, while Section 6 presents and discusses the parameter estimates, along with counterfactual policy experiments exploring the consequences of alternate border enforcement strategies. Section 7 offers a conclusion.

2 Related Literature

The existing empirical work on temporary Mexican migration focuses on explaining the duration of temporary trips in the United States. The literature suggests that durations vary across educational groups, although there does not appear to be a consensus about the nature of this relationship (Reyes and Mameesh, 2002; Massey and Espinosa, 1997; Lindstrom, 1996). The size and economic characteristics of one's community of origin also matter. Empirical work suggests that the distance of an individual's home community from the United States is positively associated with trip duration (Carrion-Flores, 2006), but that migrants from larger communities and more agricultural areas tend to exhibit higher hazard rates for returning (Lindstrom, 1996; Reyes, 2004). Accumulated wealth appears to exert an additional influence on the pattern of migration, with the possession of certain assets, including land and residential property, being associated with a higher probability of returning. (Massey and Espinosa, 1997; Reyes, 2004).

The empirical literature on circular Mexican migration indicates that individuals with different characteristics tend to engage in patterns of circular migration differentiated by trip duration. It is useful to set these findings against the broader literature on the selectivity of Mexican migrants, since the structure of incentives that govern selection into any migration may also govern selection into different patterns of circular migration. Following seminal work of Borjas (1987), who uses a static Roy model as a theoretical starting point, a string of empirical studies have concluded that Mexican migrants tend to be negatively selected on the basis of human capital measures such as eduction, or are drawn from the lower tail of the Mexican earnings distribution (Borjas and Katz, 2007; Ibarraran and Lubotsky, 2007; Moraga, 2006). However, this conclusion has been challenged by studies such as Chiquiar and Hanson (2005), which argue that migrants are drawn from the middle of the Mexican wage distribution. Lacuesta (2006) and Orrenius and Zavodny (2005) also find such intermediate selection, the latter study specifically analyzing undocumented migrants. A pattern of intermediate selection can be explained theoretically when both the cost of migration and the international wage gap decline with a worker's level of human capital. Furthermore, as McKenzie and Rapoport (2007) point out, the poorest individuals may be prohibited from migrating if they are unable to borrow to pay for moving costs.

The effect of U.S. border enforcement strategy on migration behavior stands out as an important policy consideration in the empirical literature on Mexican migration. Conventional wisdom holds that more stringent border policing can reduce the population of illegal immigrants in the United States by reducing the incentives and opportunities for migrants to cross into the U.S. without documents. However, Massey et al. (2003) argue that the intensification of activities by the U.S. Border Patrol in the last twenty years has not necessarily deterred potential migrants, but has instead raised the costs of each individual trip to the U.S., causing undocumented circular migrants to take fewer but longer trips. Massey et al. (2003) ultimately conclude that, as a result of this effect, a policy of tight border enforcement may be counterproductive. This line of argument has found further empirical support in the work of Angelucci (2005), who indeed finds that higher levels of border enforcement are associated with lower hazard rates for return migration. Using MMP data, Angelucci (2005) finds that the deterrent effect of increased border enforcement roughly cancels the lengthening of migratory trips. Using INS apprehensions data, Hanson and Spilimbergo (1999) also find that increased border enforcement is associated with a larger number of apprehensions at the border, suggesting that tougher border enforcement may increase the interception risks associated with an illegal entry.

Following Djajic and Milbourne (1988), a number of studies have developed models of circular migration, many inspired by the experiences of temporary migrants in European host countries such as Germany and the United Kingdom. In the framework of Djajic and Milbourne (1988), individuals can migrate at the beginning of their lives and choose a time to permanently return. Individuals migrate in this model because of higher wages in the foreign country, and they return because of a preference for consumption in the home country. Berninghaus and Seifert-Vogt (1993) provide a rigorous theoretical treatment of this type of model, which is characterized by "target-saving" behavior in which migrants remain in the foreign country until they have accumulated some optimal stock of savings. [2]

A number of papers examine models with different motivations for return migration, most preserving the one-trip structure. Dustmann and coauthors extend a model similar to that of Djajic and Milbourne, considering several incentives for return which are catalogued in Dustmann and Weiss (2007). Migrants may return home because they have accumulated skills in the foreign country which yield a higher return in the home country's labor market. Alternately, migrants may accumulate savings in the foreign country and return in order to establish a business or otherwise invest their savings in a productive enterprise which they can only access in the home country.[3] Price differences between the home country and the foreign country could also motivate this pattern. Furthermore, as Yang (2006) discusses, favorable exchange rate shocks may induce migrants to return home and convert assets accumulated abroad into home currency for consumption or investment. Recent studies, including Bellemare (2007) and Kirdar (2004), use data on migrants in Germany to estimate

[2] Starting with Piore (1979), the idea that temporary migrants act primarily as target savers has been a popular theoretical starting point.

[3] See Dustmann and Kirchkamp (2002) and Mesnard (2004)

structural models of one-trip migration and asset accumulation that incorporate some of these motives.

Although the existing literature has explored a number of different motivations for return migration, most have assumed that a migrant must remain home permanently after coming back from a trip to the foreign country. As Bellemare (2007) notes, this may be a reasonable assumption when analyzing temporary migration to Europe, since this one-trip pattern seems to typify the experiences of major migrant populations such as Turkish workers in Germany. However, when analyzing Mexican migration to the United States, the prominence of circularity in the behavior of undocumented migrants makes this assumption undesirable.

Colussi (2006) develops and estimates an equilibrium model allowing for repeated circular migration and network effects. Colussi's results suggest that the size of the network of migrants from one's community in the United States significantly affects the incentive to migrate. However, to simplify estimation, Colussi does not allow for asset accumulation and uses data from three villages surveyed before 1990. Both Angelucci (2005) and Hill (1987) consider more limited models of repeated circular migration with savings, but neither study attempts to estimate structural parameters. Rendon and Cuecuecha (2007) do estimate a model of repeated circular migration with asset accumulation, and of all existing studies, theirs comes the closest to the approach taken here.

The estimation results presented in this paper make several unique contributions to this existing literature. Since the empirical model explicitly models the non-stationary environment of the 1990s, the results provide the first structural estimates of the effect of border enforcement on migration behavior. By allowing for heterogeneity in the underlying migration parameters, the model reveals that border enforcement only altered the behavior of a certain group of individuals. Unique counterfactual simulations also examine the consequences of exchange rate fluctuations on circular migration patterns. These results highlight the special role that asset accumulation plays in making return migration behavior sensitive to exchange rate movements.

3 A Model of Repeated Circular Migration

Consider an environment in which there are two countries, "home" and "foreign." A worker lives in a discrete-time world and has a known lifetime of T periods. The worker begins life in the home country with an initial stock of financial assets, k_1, which is denominated in real units of the home country's currency. Every period the worker must make location and consumption decisions. Workers supply labor inelastically every period and receive a wage drawn from the labor income distribution of their current country of residence. I assume that an individual worker's real income at time t in the home country, w_t^h, and his or her real income at time t in the foreign country, w_t^f are independently log-normally distributed as: $log(w_t^h) \sim N(\mu_h, \sigma_h^2)$, $log(w_t^f) \sim N(\mu_f, \sigma_f^2)$. The real exchange rate, ex_t, governs the conversion of real units of the foreign currency into real units of the home currency in any period t. The real exchange rate is assumed to be log-normally distributed as: $log(ex_t) \sim N(\mu_e, \sigma_e^2)$.

3.1 Period Utility and the Cost of Migration

A logarithmic utility function characterizes a worker's preferences over consumption in both the home county and the foreign country: $u(c_t) = \log(c_t)$. Note that the utility function has the same argument in both countries, c_t, which measures a physical quantity of the consumption good. In the home country, the quantity of consumption chosen is equal to the level of consumption expenditure $\mathcal{C}_{h,t}$, which is denominated in real units of the home country's currency: $c_t = \mathcal{C}_{h,t}$. However, we must account for price differences when comparing consumption levels in the home and foreign countries. Therefore, if $\mathcal{C}_{f,t}$ is a level of consumption expenditure in the foreign country, denominated in real units of the foreign country's currency, then the quantity of the consumption good purchased with this level of expenditure is $c_t = \frac{\mathcal{C}_{h,t}}{ppp_t}$, where ppp_t is a purchasing power parity conversion rate. We assume for the moment that ppp_t takes some constant value, $ppp_t = ppp$ for all t.

Individuals not only derive utility from consumption, but also from amenities in their place of residence. Individuals may exhibit a preference for one region over another, and this is captured by a random utility shock, η_t. Each period in the foreign country, an individual draws a value of this shock from a normal distribution: $\eta_t \sim N(\mu_\eta, \sigma_\eta^2)$. Although μ_η could be either positive or negative in theory, one would expected that μ_η is negative, reflecting a preference for location in one's home country. One could therefore interpret η_t as the disutility that follows from coping with certain features of the foreign country, including unfamiliar people, languages, and cultures. Let L_t indicate the worker's location in period t, so that $L_t = 1$ if the worker chooses to locate in the foreign country in period t and $L_t = 0$ if the worker chooses to locate in the home country in period t. We can thus define a single period utility function, $\mathcal{U}(c_t, L_t)$ which is a function of consumption and location choices:

$$\mathcal{U}(c_t, L_t) = \begin{cases} log(c_t) & \text{if } L_t = 0 \\ log(c_t) + \eta_t & \text{if } L_t = 1 \end{cases} \tag{1}$$

Every time the migrant enters the foreign country, he or she pays a monetary migration cost, λ_t, drawn from a log-normal distribution: $log(\lambda_t) \sim N(\mu_\lambda, \sigma_\lambda^2)$ Since this study focuses on patterns of undocumented migration, λ_t can be thought of as measuring the costs of an undocumented border crossing. Hence, λ_t is paid upon entry into the foreign country but not again upon return to the home country. The monetary costs of an undocumented border crossing may include the fees paid to human smugglers, or the cost of subsistence during the border crossing process. The λ_t term may also be interpreted as capturing the monetary equivalent of the psychological costs endured during a clandestine border crossing. It is assumed that λ_t is measured in real units of the foreign country's currency.[4]

3.2 Capital Markets and Asset Accumulation

Following McKenzie and Rapoport (2007), we assume that individuals are unable to borrow in this model. Although sharp, this assumption may reasonably capture the credit market imperfections faced by individuals in the poor areas prone to undocumented migration. Although individuals cannot borrow, they can save financial assets, which accumulate according to the interest factor R. All assets held by individuals are kept in the home country, and R reflects the prevailing interest rate there. Let k_t denote the asset stock at the start of period t, denominated in units of real home-country currency at time t. When the individual is located in the home country, assets accumulate according to the following equation:

$$k_{t+1} = R[k_t + w_t^h - \mathcal{C}_{h,t}] \tag{2}$$

However, when the individual is located in the foreign country, any earnings that he or she saves are immediately remitted back to the home country to join the individual's existing pool of assets. Hence, if a consumer begins period t in the foreign country with a domestic asset stock k_t, and chooses to spend $\mathcal{C}_{f,t}$ on consumption in the foreign country, next period's capital stock evolves to:

$$k_{t+1} = R[k_t + ex_t(w_t^f - \mathcal{C}_{f,t})] \tag{3}$$

If $(w_t^f - \mathcal{C}_{f,t}) > 0$, so that the individual is saving some part of the period's wages, this quantity of savings is converted into units of the home country's currency at the current exchange rate and remitted back home. Alternately, if $(w_t^f - \mathcal{C}_{f,t}) < 0$ the individual consumes more than the current wage and draws down the asset stock. This would be accomplished by transfers of financial assets from the home country to the foreign country.

In reality, individuals can choose to take some fraction of their assets with them to the

[4] This assumption seems justified for two reasons. First, as indicated in the empirical work by Gathmann (2008), Donato et al. (1992), and others, fees paid to smugglers are often denominated in dollars. Additionally, costs related to subsistence in the United States during travel and job search at the start of a trip are also likely to be denominated in dollars.

foreign country, and they do not have to remit all of their savings home every period. These restrictive assumptions are made for three reasons. First, they simplify the problem by eliminating the need to model the individual's choice of how much wealth to take along to the foreign country. They also eliminate the need to keep track of two separate state variables measuring assets (assets held at home and assets held in the foreign country). Secondly, it is likely that the access to foreign capital markets that undocumented immigrants enjoy is extremely limited. Finally, these assumptions seem broadly consistent with the typical pattern of behavior described in the literature on Mexican migration. Wealth accumulated by temporary Mexican migrants is typically intended for the purposes of acquiring Mexican assets such as land and housing.

3.3 The Migrant's Problem

We are now in a position to define the structure of the individual migrant's decision problem. At the beginning of an arbitrary period t, the worker begins at the location chosen in the previous period, L_{t-1}, with a stock of assets, k_t. Individuals begin life with some initial stock of assets, k_1. Each period, the worker must choose to either remain in the current location or move. Individuals make this decision after receiving draws of every variable that can be reasonably known in their current location, but without knowledge of variables specific to the other location. Thus, if $L_{t-1} = 0$, individuals receive draws of w_t^h,λ_t, and ex_t before making a location decision, but realizations of w_t^f and η_t are only known if migration occurs in period t. Likewise, if $L_{t-1} = 1$, individuals receive draws of w_t^f,η_t, and ex_t, but not w_t^h before making a location decision in period t.[5] After making a location decision, the worker receives information about the remaining stochastic variables and then makes a consumption decision.

First consider an individual who begins period t in the home country and must choose to either stay at home or move to the foreign country. Let $V_t^h(k_t|\Omega_t^h)$ denote the value of beginning period t in the home period with capital stock k_t, given the information set $\Omega_t^h = \{w_t^h, \lambda_t, ex_t\}$, and let $V_t^f(k_t|\Omega_t^f)$ denote the value of beginning period t in the foreign country with a domestic asset stock of k_t, given the information set $\Omega_t^f = \{w_t^f, \eta_t, ex_t\}$. These value functions are derived from the maxima of the expected values of moving and staying in each case. Let $\nu_t^{hh}(k_t|\Omega_t^h)$ and $\nu_t^{hf}(k_t|\Omega_t^h)$ represent the expected values associated with staying in the home country and moving to the foreign country in period t if one begins that period in the home country with asset stock k_t. Then assuming that the workers make consumption decisions so as to maximize the present discounted value of lifetime utility, and

[5]When $L_{t-1} = 1$, it does not matter if we assume that λ_t is known or unknown to the individual since this information will not alter the optimal location decision.

assuming a utility discount factor of β, the expected values of staying and moving can be defined as:

$$\begin{aligned}\nu_t^{hh}(k_t|\Omega_t^h) &= \max_{\mathcal{C}_{h,t}} \log(\mathcal{C}_{h,t}) + \beta E_{\Omega_{t+1}^h}\left[V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right] \\ & s.t.\ \ k_{t+1} = R[k_t + w_t^h - \mathcal{C}_{h,t}] \\ & \quad \mathcal{C}_{h,t} \leq k_t + w_t^h\end{aligned} \tag{4}$$

$$\begin{aligned}\nu_t^{hf}(k_t|\Omega_t^h) &= E_{\eta_t, w_t^f}\left[\max_{\mathcal{C}_{f,t}} \log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + \eta_t + \beta E_{\Omega_{t+1}^f}\left[V_{t+1}^f(k_{t+1}|\Omega_{t+1}^f)\right]\right] \\ & s.t.\ \ k_{t+1} = R\left[k_t + ex_t(w_t^f - \mathcal{C}_{f,t} - \lambda_t)\right] \\ & \quad \mathcal{C}_{f,t} \leq \frac{k_t}{ex_t} + w_t^f - \lambda_t\end{aligned} \tag{5}$$

Since a worker cannot borrow to finance migration, he or she is constrained to remain in the home country when $\frac{k_t}{ex_t} < \lambda_t$. We can therefore define $V_t^h(k_t|\Omega_t^h)$ as:

$$V_t^h(k_t|\Omega_t^h) = \begin{cases} \nu_t^{hh}(k_t|\Omega_t^h) & \text{for } \frac{k_t}{ex_t} < \lambda_t \\ \max\{\nu_t^{hh}(k_t|\Omega_t^h), \nu_t^{hf}(k_t|\Omega_t^h)\} & \text{for } \frac{k_t}{ex_t} \geq \lambda_t \end{cases} \tag{6}$$

When the worker begins period t in the home country, the optimal location choice given the information set, $L_t^*(k_t, \Omega_t^h|L_{t-1}^* = 0)$, can then be derived as follows:

$$L_t^*(k_t, \Omega_t^h|L_{t-1}^* = 0) = \begin{cases} 1 & \text{if } \frac{k_t}{ex_t} \geq \lambda_t \text{ and } \nu_t^{hf}(k_t|\Omega_t^h) > \nu_t^{hh}(k_t|\Omega_t^h) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The optimal consumption level can be obtained from the solutions to the consumption-savings problems defining $\nu_t^{hh}(k_t|\Omega_t^h)$ and $\nu_t^{hf}(k_t|\Omega_t^h)$.

Now let us consider an individual who begins period t in the foreign country and must choose to either stay abroad for the current period or return home. Given the level of assets at the start of period, k_t, the value of moving to the home country, $\nu_t^{fh}(k_t|\Omega_t^f)$, and that of staying in the foreign country, $\nu_t^{ff}(k_t|\Omega_t^f)$, can be derived as follows:

$$\begin{aligned}\nu_t^{fh}(k_t|\Omega_t^f) &= E_{w_t^h}\left[\max_{\mathcal{C}_{h,t}} \log(\mathcal{C}_{h,t}) + \beta E_{\Omega_{t+1}^h}\left[V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right]\right] \\ & s.t.\ \ k_{t+1} = R[k_t + w_t^h - \mathcal{C}_{h,t}] \\ & \quad \mathcal{C}_{h,t} \leq k_t + w_t^h\end{aligned} \tag{8}$$

$$\nu_t^{ff}(k_t|\Omega_t^f) = \max_{\mathcal{C}_{f,t}} \log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + \eta_t + \beta E_{\Omega_{t+1}^f}\left[V_{t+1}^f(k_{t+1}|\Omega_{t+1}^f)\right] \tag{9}$$
$$s.t.\ k_{t+1}^f = R[k_t + ex_t(w_t^f - \mathcal{C}_{f,t})]$$
$$\mathcal{C}_{f,t} \leq \frac{k_t}{ex_t} + w_t^f$$

We can thus define $V_t^f(k_t|\Omega_t^f)$ as $\max[\nu_t^{hf}(k_t|\Omega_t^f), \nu_t^{fh}(k_t|\Omega_t^f)]$. The optimal location decision then follows the rule:

$$L_t^*(k_t, \Omega_t^f|L_{t-1}^* = 1) = \begin{cases} 1 & \text{if } \nu_t^{ff}(k_t|\Omega_t^f) > \nu_t^{fh}(k_t|\Omega_t^f) \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

The optimal consumption level can be obtained from the solutions to the consumption-savings problems defining $\nu_t^{ff}(k_t)$ and $\nu_t^{fh}(k_t)$.

Workers in this model make migration decisions by comparing the marginal benefits and marginal costs of spending an extra period in the foreign country. A migrant must pay λ_t for each trip taken, and for each additional period that the migrant stays in the foreign country, he or she is expected to incur some loss in utility as long as $\mu_\eta < 0$. By contrast, each period of residence in the foreign country is expected to result in a higher real wage measured in the home country's currency.

Consider an individual who begins period t in the home country, and suppose that μ_f is sufficiently high so that workers have an incentive to migrate. Because of the borrowing constraint, migration will only occur if k_t exceeds $ex_t\lambda_t$. In general, there also exists a threshold asset level, k_t^{hf} such that if $k_t > k_t^{hf}$, the worker chooses to stay home in period t. Since the marginal utility of consumption is declining, workers with sufficiently high asset stocks stay home because as k_t gets large, the extra utility that can be gained by accessing the higher wages of the foreign country is outweighed by the disutility of leaving the preferred home country. This model thus predicts that migrants will be drawn from the middle of the wealth distribution, since very poor workers may never be able to afford migration while very wealthy workers have no incentive to migrate. This result is analogous to the pattern of intermediate selection found in Chiquiar and Hanson (2005), although here migrants are selected on the basis of wealth as opposed to human capital.

The cost of migration, λ_t, and the home country wage distribution not only serve an important role in governing the selectivity of migrants, but they also affect migration dynamics by determining an individual's waiting time until his or her first migration. If workers cannot afford to migrate at the beginning of their lives, they must remain at home and save until they either accumulate assets sufficient to pay the randomly drawn cost of migration. Individuals beginning life with the lowest asset levels relative to the cost of migration will either be unable to afford migration, or will migrate later in life than those with larger initial asset endowments.

Once an individual has migrated, two features of the model encourage a return. First, return migration is encouraged by the diminishing marginal value of assets. While in the foreign country, the individual must decide each period whether residence in the foreign country for an additional period is desirable. Depending on the particular realization of w_t^f that the individual faces, staying for one more period allows the individual to gain a premium over the expected home country wage. However, because the period utility function is concave with respect to consumption, the marginal utility associated with gaining this premium declines as the individual's asset stock increases. If an individual accumulates assets while working in the foreign country, the marginal benefit associated with continued residence in that country declines with each period. The η_t shock represents part of the marginal cost, in terms of utility, of continued residence in the foreign country. As an individual's length of stay in the foreign country increases, the expected value of η_t remains constant while the marginal benefit of continued residence in the foreign country is falling. In general, assuming a negative value for μ_η, there exists some threshold level of assets, k_t^{fh} such that if $k_t > k_t^{fh}$, the marginal value of accessing the foreign country wage premium is less than the marginal disutility associated with continued presence in the foreign country.

A second incentive encouraging return migration relates to the difference between the exchange rate and the rate of purchasing power parity. By earning w_t^f in the foreign labor market, an individual in the model can purchase $\frac{w_t^f}{ppp}$ units of the consumption good in the foreign country. However, this same wage, w_t^f can purchase $ex_t w_t^f$ units of the consumption good in the home country. As long as $ex_t ppp > 1$, the worker's wages from the foreign country are able to purchase a larger quantity of the consumption good in the home country than in the foreign country. In this situation, the exchange rate acts as a multiplier for foreign wages which only becomes realized when the individual returns to the home country to purchase the consumption good.

The incentives shaping migration and return decisions make patterns of repeated circular migration possible in this model. An individual who migrates and builds an asset stock through savings may eventually reach some target level of assets, k_t^{fh}, at which point the marginal utility associated with access to the higher wages in the foreign country no longer outweighs the marginal disutility of living there and facing higher prices for another period. When this happens, the migrant returns to the home country. Period after period, if k_t remains above some threshold level, k_t^{hf}, the individual will remain at home. However, if the individual's rate of consumption outstrips the wage draw and interest income at home, his or her asset stock will decline. When k_t reaches k_t^{hf} in a given period, the individual again decides to migrate, resetting the cycle. The next section describes the numerical solution of the model and provides examples of some parameterizations that generate this pattern of repeated circular migration.

3.4 Numerical Solution

3.4.1 Value Function Approximation

The model outlined in the previous section can be solved recursively starting with the value functions for the terminal period. Assuming that there is no bequest motive, then for all values of k_{T+1}, Ω^h_{T+1}, and Ω^f_{T+1} we can set

$$V^h_{T+1}(k_{T+1}|\Omega^h_{T+1}) = V^f_{T+1}(k_{T+1}|\Omega^f_{T+1}) = 0$$

In principle, one could estimate a terminal value in the model as a function of state variables. However, unreported estimation results suggest that changing in the terminal value assumption (by adding a retirement spell), did not substantially alter parameter estimates. The zero terminal value assumption is thus maintained for convenience. Both $V^h_T(k_T|\Omega^h_T)$ and $V^f_T(k_T|\Omega^f_T)$ are functions which are computationally inexpensive to evaluate, and they can be used to approximate $E_{\Omega^h_T}[V^h_T(k_T|\Omega^h_T)]$ and $E_{\Omega^f_T}[V^f_T(k_T|\Omega^f_T)]$, which can in turn be used in the approximation of the value functions defining $V^h_{T-1}(k_{T-1}|\Omega^h_{T-1})$ and $V^f_{T-1}(k_{T-1}|\Omega^f_{T-1})$. We can continue approximating the value functions associated with successively earlier periods until the necessary value functions have been approximated for all t. Two methods are employed to increase the speed of the numerical solution. First, to minimize the computational burden of calculating expected values with respect to the stochastic variables in the model, all expected values are approximated by discretizing the distributions of the random variables in the model. Secondly, function approximation is carried out using linear interpolation methods and the discretization of the consumption decision. Sections A.1-A.3 in the Appendix describe these methods in greater detail and offer a graphical example of the approximated value functions for some reasonable parameter values.

3.4.2 The Role of Key Parameters in Shaping the Pattern of Migration

One of the critical theoretical predictions to emerge from one-trip models of temporary migration is that the cost of migration is expected to be positively related to the length of time that a migrant spends in the foreign country. [6] In a one-trip model, if the cost of migration increases, migrants must spend a longer amount of time in the foreign country,

[6] See Djajic and Milbourne (1988) for the derivation of this result

accumulating extra wealth to recoup this cost. Argumentation in this vein has served as the backbone for one popular critique of U.S. border policy. Massey et al. (2003) contend that the deterrent effect of border enforcement is small, and that increases in the cost of migration caused by intensified border enforcement should increase the length of stay of undocumented migrants in the United States. This would suggest that attempts to reduce undocumented immigration through tougher border enforcement may be counterproductive if they induce migrants to spend more of their lives in the United States.

Although one-trip models of temporary migration generate a clear positive relationship between the cost of migration and the total amount of time a migrant spends in the foreign country, it is not clear that this result and the policy implications that flow from it, survive when we consider a model of repeated circular migration. We are therefore interested in assessing the effect of changes in μ_λ on the number of trips that an individual is expected to take, as well as the fraction of this individual's time that is spent in the foreign country. Additionally, we are interested in examining the effect of changes in μ_η on these same measures of the pattern of migration. Factors that could be interpreted as influencing μ_η, such as cultural similarity between the two counties or the prevalence of the migrant's language in the foreign country, might be affected by policymakers, and so μ_η also represents a parameter of interest.

To investigate the effect of model parameters on pattern of migration generated by the model, we can generate a number of simulated migration histories for a reasonable set of parameters and record the average number of trips and the average fraction of a simulated individual's lifetime spent in the foreign country. Figure 1 illustrates the effect of changes in the parameters related to the expected cost of migration, μ_λ, and the expected level of the location preference shock, μ_η, on the average number of trips, average trip duration, and average fraction of time spent abroad for 1000 simulated individuals observed over the course of a $T = 50$ horizon.

Panels 1 and 2 of Figure 1 show that, starting from low levels of μ_η, increases in this parameter tend to increase the average number of trips, and the trip duration, and the average fraction of time spent in the foreign country. As μ_η increases, the mean disutility associated with residing in the foreign country declines. Migrants stay longer in the foreign country because it is less costly in utility terms. However the relationship between the number of migratory trips per year and μ_η is non-monotonic. At first, as μ_η increases, some individuals who where previously non-migrants decide to migrate, and the number of trips increases as people choose to take one or more migratory trips. However, continued increases in μ_η reduce the incentives for individuals to return, causing them to consolidate multiple trips and migrate on a more permanent basis. This results in the hump-shaped pattern between μ_η and trips per year. In the limit, as μ_η gets very large and positive, all migrants take only one permanent trip.

Panels 3 and 4 of Figure 1 suggests that, as μ_λ rises, the average number of trips taken by a potential migrant decreases. This result is expected since λ is the price of a migratory trip. Panel 3 suggests that as μ_λ increases, average trip duration increases. This occurs because after an increase in λ, a new migrant has a lower asset stock and faces a higher marginal utility to wealth. Thus, the individual will choose to stay in the foreign country and save assets longer before returning. Panel 4 shows that, given one particular parameterization, the average fraction of one's life spent in the foreign country seems to monotonically decline as μ_λ increases. As migration costs increase, individuals take fewer, but longer, trips. Here the reduction in trips outweighs the increase in trip durations.

The simulation results in these Panels do not suggest that higher migration costs, perhaps induced by more aggressive border policing, can actually cause individuals to spend more total time abroad. Yet, the model is capable of generating such a pattern of behavior. Panel 5 of Figure 1 again considers simulation results tracking the average time spent abroad as μ_λ increases. In contrast with the simulations in Panel 4, however, the mean and standard deviation of the foreign utility shock, μ_η and σ_η, have now been changed so that on average, the utility shocks are less negative and have a lower standard deviation. In this case, increasing the cost of migration causes individuals to spend more time overall in the foreign country. The increase in trip durations outweighs the reduction in migratory trips to increase the average time spent abroad. Thus, the model is capable of generating patterns of migration in which an increase in the cost of migration can either increase or decrease the total amount of time that potential migrants spend abroad. This relationship depends on the relative size and sign of μ_η and σ_η, and estimating the parameters of the model using Mexican data can thus shed light on which pattern holds for potential Mexican migrants.

4 Data

Every year since 1987, the Mexican Migration Project (MMP) has conducted household interviews in Mexican communities.[7] The database also includes survey responses from a pilot project conducted in 1982 and 1983. The data used here are those included in the MMP124 database, which includes 124 surveyed communities. After selecting a particular community for inclusion in the database, the Project randomly selects households within that community for the survey. For certain communities, the Project also attempts to survey a

[7]The Project is jointly administered by researchers from the University of Guadalajara and Princeton University. For more details, see http://mmp.opr.princeton.edu

set of households that are now living in the United States.

Using essentially the same questionnaire in all years, the MMP collects data on household and community level demographic and economic variables and the migration histories of the household members, with more detailed data on the most recent migratory trip taken by each member. Some survey items, such as the income of the household head, are recorded as of the time of the interview. However, the survey also requests a detailed, self-reported life history from household heads recording some economic, demographic, and migration variables for every year in their lives. Crucially, the data allow one to track whether or not a household head made a new trip in a given year, what documentation, if any, was used in making such a trip, and the number of months spent in the U.S. each year.

In the following empirical analysis, I restrict attention to the period after the passage of the Immigration Reform and Control Act of 1986. By offering an amnesty for undocumented immigrants meeting certain residency requirements before 1986, the Act created unique incentives for undocumented migration before its passage. Since this event is beyond the scope of the model developed here, I seek to explain the behavior of men reaching maturity after 1986. In the theoretical model of the previous section, agents begin life as fully mature agents at initial time $t = 1$. Applying this model to the MMP data requires one to decide when the adult life of an individual migrant begins. Previous studies working with MMP data, such as Colussi (2006), have defined adulthood in this sense as beginning at 15 years of age. This is accepted here as a reasonable ad hoc benchmark with a few modifications. First, I make use of a variable in the MMP data which indicates the year in which an individual formally entered the labor market for the first time. The first year of adulthood is therefore define as the the latest of these three years: the year the individual turned 15 years old, the first year of labor force participation, the year in which the individual's eduction was completed. The year in which eduction was completed is included in this set because I assume an individual's level of education to be an exogenous variable and make no attempt to model the endogenous acquisition of education.

The main sample of this study consists of 1401 observations of the life histories of male household heads who reached adulthood during or after 1987. This sample only includes those individuals observed as adults for at least 5 years over the period 1987-2000. The sample is restricted to non-migrants and those individuals observed making undocumented migrations to the United States, or those who migrated to the United States as tourists[8] The frequency of legal migration is small in this sample. Only 3.4% of the individuals otherwise meeting the above requirements are observed making a legal trip over the period 1987-2000.

[8] The vast majority of individuals who claim to be tourists in the sample identify the "place of job" as being in the United States.

These individuals are included in the sample, but I only consider their behavior before the year of their first legal migration. Obtaining access to a legal visa is thus assumed to be an exogenous, unforeseen event whose prospect does not significantly affect undocumented migration behavior in this sample. The sample is also restricted to men because women constitute a relatively small portion of household heads in the data, and because women are likely to face a different set of incentives in migrating than men.

4.1 Data Concerns and Sampling Weights

Two potential problems with the use of the MMP data relate to the selection of communities for the survey and the problem of absent migrants. The Project does not randomly select the communities involved in its surveys, but instead employs a method that "targets specific communities for intensive study." (Massey et al., 2003) Early waves of the MMP surveys focused on communities in the high-migration areas of West-Central Mexico. This focus raises the concern that the MMP data may over-represent households prone to migration. This concern is partially alleviated by the inclusion of new regions and communities in each successive year of the Project's survey. New survey locations are chosen to "build into the sample variation with respect to population size, geographic location, climate, economic base, social structure, and ethnic composition." Massey et al. (2003).

Another concern when using the MMP data is selection bias caused by the absence of migrants from the targeted communities at the time of the survey. The MMP attempts to deal with this problem in two ways. First, the surveys are administered during winter months, since circular migrants tend to return to Mexico during this part of the year. Additionally, after conducting a survey in a particular community, the MMP attempts to locate migrants from that community in the U.S. and administer the survey to these individuals. This allows even permanent migrants to be included in the MMP data.

Despite the problems associated with the MMP, it does provide the richest data available on circular migration dynamics between Mexico and the United States. No other data set contains as much information on the timing, duration, and number of migratory trips, especially for individuals who were young adults during the 1990s. Indeed, this has been the primary data set used to investigate temporary Mexican migration (Colussi, 2006; Rendon and Cuecuecha, 2007; Angelucci, 2005). This justifies the use of this data, although a proper weighting scheme may be necessary to mitigate the effects of the sampling procedure. The MMP does include sampling weights. However, these do not address the the concerns about the representativeness of the MMP sample, and do not necessarily provide proper weights to the households surveyed in the United States. To address these problems, I construct a set of sampling weights based on the distribution of young male children in the 1970 Mexican Census. Since most of the sample used here consists of men who were young children during the early 1970s, I use data from the Mexican census on the distribution of male children across regions and community sizes to re-weight the MMP sample. Section A.4 of the Appendix contains a detailed discussion of how I construct these Census-based weights.

4.2 Descriptive Statistics

Table 1 reports summary statistics on a number of demographic variables for those individuals in the sample. Educational attainment is divided into five categories: 0-3 years, 4-6 years, 7-9 years, 10-12 years, and more than 12 or years.[9] These categories correspond roughly to the degree system in the Mexican educational system, where primary schooling is completed after 6 years, lower secondary schooling is completed after 9 years and secondary education is completed after 12 years. Levels of education in our sample are concentrated in the intermediate ranges. Indeed, the majority of individuals in the sample have either 4-6 years or 7-9 years of schooling.

The MMP data allow us to divide communities in the following four types, which differ by size and urbanity: Rancho, Town, Smaller Urban Area, and Metropolitan Area. This categorization, although crude, divides localities into groups that differ substantially in terms of earnings opportunities or residential amenities.

The Year Born variables in Table 1 indicate when individuals in the sample were born. As noted earlier, most of the sample was born in the 1970s. The average individual in the sample is observed for just under 10 years. Table 1 also reports whether or not an individual owned any property at the time they reached adulthood. Just over 6% of the sample owned property when reaching adulthood. Additionally, we observe that about 8% of the individuals in the sample had a father who migrated before the individual entered the sample. This provides at least some measure of the kind of family networks available to individuals that might increase the incentives to migrate (Colussi, 2006).

I describe the pattern of migration using four basic measures: the time until a first migration (if any), the observed fraction of a migrant's adult life spent in the U.S., and the average number of trips taken by the individual over the course of their observed adult life, and the average duration of each trip taken by migrants. Table 2 presents summary statistics of variables related to the pattern of migration exhibited by individuals in the sample. To get a sense of the prevalence of migration in the sample, we could simply examine the number of migrants compared to non-migrants in the sample. Table 2 reports the distribution of

[9]Individuals with more than 16 years of education are excluded from the sample

the observed number of migratory trips to the U.S. for the whole sample and for the subset with any migration experience. About 39% of individuals in the whole sample have some migration experience, and of these migrants, about 27% are observed taking 2 or more trips to the Unites States over the sample period.

An alternate way to characterize the prevalence of migration is to define a set of variables $\{m_i^j\}_{j \in J}$ such that each m_i^j takes a value 1 if individual i has migrated by the end of age j, and a value of 0 otherwise. Comparing the mean values of these variables also gives us some idea of how long individuals are waiting to undertake their first migration. Additionally, let δ_i represent the fraction of individual i's observed life (in months) that has been spent in the United States, and let τ_i represent the number of trips taken by individual i divided by their number of years they are observed in the sample. The τ_i variable can also be thought of as the average number of trips taken per year.

Table 2 reports the sample means and standard deviations for the variables m_i^j, δ_i, and τ_i. I also report the average duration of uncensored trips completed during the sample period. Table 2 reports both the average completed duration, and the average duration if the trip is an individual's first trip to the United States. Although 10% of the sample migrated by age 17, this increases to around 25% by age 21, and then to approximately 31% by age 25. It should be pointed out that since individuals enter and leave the sample at different ages, these age variables are computed with different sample sizes, and thus the m_i^j need not be strictly increasing in j. The δ_i measure is perhaps more informative when it is considered only for the migrants in the sample. Among migrants, the mean of δ_i is about 0.38, suggesting that the migrants in the sample spend a little more than a third of their adult lives in the United States. Looking at τ_i and again restricting our attention to the migrants in the sample, we see that they take on average about 1.5 trips every ten years. The average trip lasts about two years, but the average first trip lasts slightly longer. This suggests that subsequent trips tend to be shorter than the average first trip to the United States.

Table 3 reports the means of the waiting time variables for different education levels level and community types. Urban communities are defined as those located in either Small Urban or Metropolitan areas. Individuals with education levels falling into the 4-9 year range tend to have the highest migration rates, and the steepest age-migration profile of any of the three education groups considered here. Indeed, individuals with more or less education have lower rates of migration at almost every age. This is consistent with the evidence presented by Chiquiar and Hanson (2005) that migrants tend to be drawn from intermediate portions of the skill distribution. The difference in migration behavior between individuals from Rural and Urban communities is also striking. Migration rates are substantially higher for individuals from Rural communities at every age level. Furthermore, individuals from Rural areas tend to take longer first trips to the United States, staying on average about 6 months longer than someone taking a first trip from an Urban area.

5 Estimation Strategy

5.1 Empirical Specifications

I assume that individuals face a finite horizon that lasts 50 years, spanning the ages 15-64. Let a_i^{adult} represent the age at which individual i is considered an adult in the sample. For the purposes of estimation, individual i possesses a finite horizon of $y_i^o = (65 - a_i^{adult})$ years, where y_i^o represents the number of years that i is observed in the sample. The unit of time in the model is one year.

Apart from parameters related to earnings and initial wealth, there are four parameters of the structural model: μ_η, σ_η, μ_λ, and σ_λ. In the empirical model, I assume that the population is heterogeneous with respect to the parameters. Specifically, I assume that each individual belongs to a type, κ, which is unobserved, and the basic model parameters are allowed to vary with an individual's type. I assume that the cost of migration is a function of the intensity of U.S. border enforcement, B_t, where this is measured by the number of employees on the Border Patrol's payroll for operations on the Southern border in year t, as collected by the Transactional Records Access Clearinghouse of Syracuse University.[10]. The first panel of Figure 2 presents a plot of this variable over the period 1986-2005. The growth rate of the payroll increases significantly after 1995, reflecting a U.S. policy response to the Mexican Peso Crisis. The cost of migration that an individual of type κ faces in period t is then modeled as:

$$\log \lambda_{\kappa,t} = \mu_\lambda^\kappa + \lambda_b^\kappa B_t \tag{11}$$

Randomness in $\lambda_{\kappa,t}$ is induced by randomness in B_t, so σ_λ is not estimated. This means that for each type, there are four migration parameters to be estimated: μ_η^κ, σ_η^κ, μ_λ^κ, and λ_b^κ.

To model expectations about the real exchange rate, ex_t and the level of border enforcement along the U.S.-Mexican border, B_t, I assume that agents possess enough information to correctly predict the time-trend of these variables. Recall that Figure 2 displays the time series of B_t over the period of the sample. The second panel of this figure also plots the real exchange rate over the period 1987-2005. This series is constructed using annual data on the exchange rate and the CPI in Mexico and the U.S. from the IMF's *International Financial*

[10]This data can be found on the Clearinghouse's website:
http://trac.syr.edu/immigration/reports/143/include/rep143table2.html

Statistics. In the years before the Peso Crisis, the real exchange rate is observed to be falling. However, the exchange rate jumps up dramatically during and after 1995, only to resume a generally downward trend thereafter.

To construct expectations for B_t and ex_t, I first estimate the following annual time trend equations using OLS:

$$\log(B_t) = \gamma_0^B + \gamma_1^B t + \gamma_2^B t^2 + \gamma_3^B Crash_t + \gamma_4^B tCrash_t + \gamma_5^B t^2 Crash_t + \varepsilon_t^B \quad (12)$$

$$\log(ex_t) = \gamma_0^{ex} + \gamma_1^{ex} t + \gamma_2^{ex} t_t^{-1} + \gamma_3^{ex} Crash_t + \gamma_4^{ex} tCrash_t + \gamma_5^{ex} t^{-1} Crash_t + \varepsilon_t^{ex} \quad (13)$$

Where the deviations from the trend in each equation are assumed to be independently and identically distributed as: $\varepsilon_t^B \sim N(0, \sigma_B^2)$ and $\varepsilon_t^{ex} \sim N(0, \sigma_{ex}^2)$. The variable $Crash_t$ has been added as a dummy variable indicating years during and after the Peso crisis of 1995 to capture changes in both the real exchange rate and U.S. border policy following that event.

Individual expectations about the trends of B_t and ex_t, and the variance of the random deviations around these trends are assumed to be consistent with OLS estimates of the parameters of Equations 12 and 13. Before the Peso Crisis, I assume that individuals expect a trends consistent with the trend regressions when $Crash_t = 0$. The Peso Crisis is taken to be an unanticipated structural shock to the economy. When the crisis hits in 1995 and for all subsequent years, individuals are assumed to instantly adjust their expectations and have beliefs consistent with the estimates of Equations 12 and 13 when $Crash_t = 1$. This type of instantaneous adjustment may abstract from a more realistic environment in which beliefs sluggishly adjust, but the severity of the peso crisis adds plausibility to the assumption that this event quickly and significantly altered individual expectations about the future of the Mexican economy and U.S. policy.

All individuals are assumed to share a common value of β. Although β could be estimated as an unknown parameter, I choose to assume an acceptable value for the discount rate and impose it throughout estimation. The estimation results that follow have been derived assuming $\beta = .96$. Two final macroeconomic parameters included in the model are the real interest rate, R, and the real rate of purchasing power parity conversion, ppp_t. The data do not include information about the rates of return on savings available to the individuals in our sample, and it is unlikely that individuals in the sample have the ability to invest assets in the full spectrum of investment opportunities in Mexico. I therefore proceed by setting R equal to the interest factor that is consistent with the average real Mexican money market rate over the period 1987-2000, as derived from nominal interest rate and CPI series from the IMF's June 2010 release of *International Financial Statistics*. This implies $R = 1.0218$. I make a similar simplifying assumption when dealing with ppp_t by setting to its value in the year 2000 as derived from OECD data and CPI data for both countries from the IMF (0.16, or about 6.11 real pesos per real dollar).

I assume that an individual can belong to one of two unobserved types.[11] The probability that an individual belongs to Type 1 is given by the following logit form:

$$Prob(\,Type = 1) = \frac{exp(X_i \gamma^p)}{1 + exp(X_i \gamma^p)} \tag{14}$$

Where X_i is a vector of variables that includes a constant, a dummy indicating if an individual's father had migration experience at the beginning of the sample, a dummy if the individual comes from an urban area, and dummies for possessing $4 - 9$ Years of Education and ≥ 10 Years of Education. Adding the education dummies to the mixing regressors allows us to explore whether costs fall with human capital, as suggested by Chiquiar and Hanson (2005).

5.2 Identification

Here I offer a quick sketch of how the model parameters can be identified from the data, although Section A.5 of the Appendix offers a more detailed discussion, with some illustrative simulations. The parameters related to the initial distribution of assets and the income processes are identified directly from data on assets in Mexico and income in the United States and Mexico. This means that for a given type, there are four basic parameters that need to be identified from migration data: μ_η, σ_η, μ_λ, and λ_b. As argued above, μ_η and μ_λ both influence the fraction of time spent in the United States, δ, and the rate of trips taken per year, τ. An observed combination of the means of δ and τ in the data can thus pin down the values of μ_η and μ_λ. Additionally, the age-migration profile, as measured by the m_i^j variables, is an additional source of identification for the cost of migration. Since individuals must save to cover migration costs, the m_i^j variables reveal how long individuals must wait before they can pay these costs. Since the variance of a migration measure such as δ is influenced by the variance of shocks to return migration incentives, the variance of δ can identify σ_η, the standard deviation of the location utility shock. Finally, the effect of border enforcement on the cost of migration, λ_b, can be identified from differences in observed migration behaviors across different birth cohorts. Different values for μ_η, σ_η, μ_λ, and λ_b for different types, along with the mixing probability parameters, can be identified by the means and variances of the basic migration measures discussed above conditional on the X_i variables that affect the mixing probabilities.

[11] I did estimate a model with more than two types, but this resulted in very imprecise estimates.

5.3 Distribution of Labor Income in Mexico and the U.S.

To estimate the distribution of labor market income in Mexico, I use data from the Encuesta Nacional de Ingresos y Gastos de los Hogares, or ENIGH. This survey is a nationally representative cross-sectional survey of household income and expenses that is administered biannually. From 1992 onwards, the survey includes surveys both rural and urban households, allowing one to account for the differences in urban and rural income levels. From the 1992 through 2000 waves of the ENIGH, I use the income data of males, aged 15-64, who are out of school, who are not self-employed, and who worked at least 20 hours in the week before the survey. For each observation, I record the monthly labor market income earned in an individual's primary job. The combined sample consists of 35,085 observations. Each period of time in the structural model represents a year. Therefore, I use the ENIGH data to construct an annual labor market income measure, and estimate a labor market income distribution that depends on age, age squared, education dummies, and whether or not an individual resides in an urban area.[12] Income also depends on a time trend with a structural break at 1995 to reflect the effects of the Peso crisis:

$$\begin{aligned}\log(w_t^{MEX}) &= \gamma_{w,0}^{MEX} + \gamma_a^{MEX} Age_{it} + \gamma_{a2}^{MEX} Age_{it}^2 + \sum_j \gamma_{e,j}^{MEX} EDU_{i,j} + \gamma_u^{MEX} Urban_i + \gamma_T^{MEX} Trend_t + \\ &\quad \gamma_{cr}^{MEX} Crash_t + \gamma_{crT}^{MEX} Trend * Crash_t + \varepsilon_{i,t}^{MEX} \qquad (15)\end{aligned}$$

Where $Crash_t$ is a dummy for years after 1994.

To estimate the labor market income distribution in the United States for undocumented migrants, I use responses from the MMP that directly ask about income while in the United States on the most recent migratory trip. After dropping individuals with missing data, there are 1,350 observations of undocumented migrants with non-zero income aged 15-64 who took trips over the period 1987-2000. The MMP data asks about the average hourly wage, the average number of hours worked per day, and the average number of days worked per week on the last trip. This can be used to construct an annual income measurement. I estimate the following income equation, which depends on age, education, and a time trend:[13]

$$\log(w_t^{US}) = \gamma_w^{US} + \gamma_a^{US} Age_{it} + \sum_j \gamma_{e,j}^{US} EDU_{i,j} + \gamma_T^{US} Trend_t + \varepsilon_{i,t}^{US} \qquad (16)$$

[12]Here an urban area is defined as a community whose population is greater than or equal to 15,000 inhabitants. This is consistent with the urban areas constructed elsewhere in this study that constructed using MMP and Mexican Census data.

[13]The square of age is omitted from the US income equation because this coefficient was very imprecisely estimated. Including this coefficient greatly increased the variance of the structural parameter estimates

The shocks $\varepsilon_{i,t}^{US}$ and $\varepsilon_{i,t}^{MEX}$ are assumed to following the normal distribution, and to be independently and identically distributed across years and individuals. Table 4 presents results from a method of moments estimation of Equations 16 and 15.[14]Monthly earnings are calculated in real dollars or pesos using CPI measures for Mexico and the U.S. from the IMF's June 2010 release of *International Financial Statistics*. The year 2000 is taken to be the base year. The estimation results for Mexican incomes present a reasonable age profile, and the coefficient estimates on the education dummy variables suggest the expected positive relationship between education and income. Incomes are substantially higher in more urban areas. The Peso crisis precipitated an immediate and severe drop in incomes. However, the estimated coefficient on $Trend_t * Crash_t$ indicates that labor incomes started to modestly recover after the crisis.

The estimation results for U.S. wages offer a few surprising results. The coefficient on Age is negative and significant, although small in magnitude. This relationship seems reasonable for most agricultural jobs and many service sector jobs. Even if older individuals gain useful experience for these jobs, they may also be less physically capable of performing on the level of a younger individual. The estimated parameters for the wage do suggest a positive relationship between eduction and labor income in the U.S., although the returns to education for the individuals in the sample appear to be much lower in the U.S. than in Mexico.

Individuals are assumed to have beliefs about the wage distributions that are consistent with the parameter estimates for Equations 15- 16. This implies that individuals have expectations of future wages that incorporate a time trend consistent with the coefficients on the $Trend_t$ variables. To avoid relying heavily on the time trend for out-of-sample estimates, I set $Trend_t$ equal to the year 2000 value for all periods after 2000 when calculating individual beliefs. For years before 1995, I model beliefs about the Mexican wage distribution as being consistent with the parameter estimates for Equation 15 assuming that $Crash_t = 0$. When the crisis hits in 1995, it is assumed that individuals instantly adjust their expectations and have beliefs consistent with the estimates of Equation 15 when $Crash_t = 1$.

5.4 Initial Wealth

In order to estimate the structural model, one must account for the initial capital stock, k_1. I assume that initial wealth is random, and is drawn from an exponential distribution.

[14]Method of Moments is used because structural estimation not only requires estimates of the variance of the wage shock, σ_ϵ, for each wage equation, but also the variance of this estimate and the covariance of this estimate and the other parameter estimates. These variance terms are more easily computed in the Method of Moments framework. The moments used are simply the set of moments implied by OLS estimation and an additional moment to match σ_ϵ^2 with the mean squared error.

Although one could estimate the parameters of the exponential distribution together with the other parameters of the behavioral model, I estimate the parameters of the wealth distribution using data from the Mexican Family Life Survey. This approach is preferable because it may be difficult to separately identify initial wealth and the cost of migration from migration behavior alone. A given level of initial wealth and a given cost of migration might produce the same age-migration profile as a lower level of initial wealth and a lower cost of migration.

We estimate the distribution of the value of assets for young households using data from the Mexican Family Life Survey (MFLS). The MFLS is a nationally representative survey of Mexican households, the only data set I am aware of recording data on wealth stocks for Mexican households. We use the data from the first wave of the MFLS, conducted in 2002. The MFLS asks respondents if they possess holdings of a set of fourteen assets classes, and then asks for the value of holdings in each class. The survey also asks for the value of any debts, and our measurement of assets if given by the value of reported assets net of any debts.[15] To best match the distribution of assets for very young individuals, we restrict the sample to male household heads between the ages of 15 and 25, who have non-missing asset data. This produces a sample of 508 individuals. Using the MFLS data, we estimate an exponential wealth distribution for very young household heads, with with an expected value given by $E[k_i \,|X^A] = \exp(-X_i^a\gamma^a)$. Here X^a is a set of regressors that includes a constant, age, a dummy if education is at least 10 years, and a dummy for any real estate property ownership. Notice that although the MMP does not have data on asset values, it does contain data on all of these regressors at the time of adulthood. Hence, the estimated wealth distribution can be used in the simulations. The parameters of the distribution can be estimated by methods of moments using moments related to conditional means. If A_i represents assets for an individual observation in the MFLS sample, then the moment conditions are simply:

$$E[X_a'(exp(-X_i^a\gamma^a) - A_i)] = 0 \tag{17}$$

Table 5 presents method of moments estimates of the γ^a parameters. As expected, the mean level of wealth rises with age, education, and property ownership. The parameter estimates suggest reasonable values for the mean and median levels of wealth. Based on these estimates, the median wealth level for an 18 year old individual with six years of education and no property is about 4,500 pesos, or roughly $450.

[15] Any negative net asset amounts are set to 0. This was only true for 4.5% of the sample used in the estimation.

5.5 Estimation

The estimation procedure followed here relies on the Method of Simulated Moments. I try to find parameters that generate simulated migration histories with summary statistics that match those observed in the data. Recall that the variables $\{m_i^j\}_{j\in J}$, δ_i, and τ_i offer a convenient characterization of the pattern of migration for an individual. Let $\mathfrak{p}_{1i}$ and $\mathfrak{p}_{2i}$ represent vectors of observed variables characterizing individual $i's$ pattern of migration:

$$\begin{aligned}\mathfrak{p}_{1i} &= [m_i^{*17}, m_i^{*19}, m_i^{*21}, m_i^{*23}, m_i^{*25}, \delta_i, \delta_i^2, \tau_i] \\ \mathfrak{p}_{2i} &= [Trip_i^{1,1}, Trip_i^{1,2}, Trip_i^{1,3}, Trip_i^{2,1}, Trip_i^{2,2}]\end{aligned}$$

The $\mathfrak{p}_{1i}$ vector contains the pattern variables defined earlier as well as the square of δ_i to pick up information about the dispersion of time spent in the U.S. The $\mathfrak{p}_{2i}$ vector contains the variables $Trip_i^{l,y}$ to better capture the durations of individual trips. These variables are dummies indicating if i is observed completing an l^{th} migratory trip that lasts y years or less. Note that the m_i^{*j} variables have been flagged with asterisks. These variables are modified to account for the fact that some people are not observed at an age j. The variable m_i^{*j} takes the value m_i^j if individual i is observed at age j, and takes the value 0 otherwise. Let X_{1i} represent a vector of characteristic variables including education dummies, cohort dummies, an urban dummy, and a dummy for whether or not an individual's father migrated before the start of the sample, and some interactions. Also, let X_{2i} be a smaller set of variables including a constant, a dummy indicating cohorts becoming adults in 1989 and later, and a dummy indicating 4-9 years of education. The full set of summary statistics used to form the moment conditions consists of: $\mathfrak{p}_i = [\mathfrak{p}_{1i} \otimes X_{1i} \;\; \mathfrak{p}_{2i} \otimes X_{2i}]$. The Section A.6 in the Appendix offers a detailed description of the full set of summary statistics.

Now, let Π^M refer to the vector of migration parameters in the structural model, so Π^M contains μ_η^κ, σ_η^κ, μ_λ^κ, and λ_b^κ for each type κ, as well as the parameters related to the mixing probabilities, γ^p. Furthermore, let $\Pi^{w,US}$, $\Pi^{w,Mex}$, and Π^A refer to the vectors of parameters governing the income distributions in the US and Mexico, and the initial asset distribution, respectively. For a given set of model parameters, I approximate the value functions for each individual given their characteristics and their year of adulthood. For each year the individual is observed, I also generate a vector of ρ draws for each of the three disturbance terms: $\varepsilon_{i,t}^\eta$, $\varepsilon_{i,t}^{Mex}$, and $\varepsilon_{i,t}^{US}$. [16] For each individual i, these vectors have length equal to y_i^o. For

[16] To construct these random vectors, we first start with three $y_i^o \times \rho$ matrices of random draws from a uniform [0,1] distribution: φ_i^{US}, φ_i^{MEX}, and φ_i^η. These matrices of draws are held fixed for each individual for every iteration on the parameters. For a given set of parameters, these matrices are used to construct ρ sequences of the random variables in the model by evaluating the inverse c.d.f. for each of these random variables at the values contained in the φ_i matrices.

each individual and for each sequence of draws, I use the approximated value functions to simulate migration behavior, generating a population of ρ simulated migration histories for each individual. Let $\widetilde{\mathfrak{p}}_{i,j}(\Pi^M, \Pi^{w,US}, \Pi^{w,Mex}, \Pi^A)$ represent the vector of migration pattern variables constructed from the j^{th} simulated history for individual i. For all of the simulations presented here, $\rho = 500$.

Given the observed migration variables and the simulated migration histories, the following represents the vector of moment conditions used in the estimation procedure:

$$g(\mathfrak{p}_i, \Pi) = \mathcal{W}_i \left[\mathfrak{p}_i - \frac{1}{\rho} \sum_{j=1}^{\rho} \widetilde{\mathfrak{p}}_{i,j}(\Pi^M, \Pi^{w,US}, \Pi^{w,Mex}, \Pi^A) \right] \tag{18}$$

Where $\mathcal{W}_i$ is the sampling weight for individual i, and Π is a combined vector of all model parameters. The Method of Simulated Moments Estimator for Π^M is then given by:

$$\Pi^{M*}_{MSM} = ArgMin_{\Pi^M} \; [\frac{1}{n} \sum_{i=1}^{n} g(\mathfrak{p}_i, \Pi)] W [\frac{1}{n} \sum_{i=1}^{n} g(\mathfrak{p}_i, \Pi)]' \tag{19}$$

Where W is a weighting matrix. The j^{th} element on the diagonal of W is the square of the ratio of the sum of weights $\mathcal{W}_i$ for all individuals to the sum of the weights used to construct the j^{th} moment in the g vector. This matrix weights the moments so that their scales are comparable as average descriptive statistics for different sub-populations. Section A.7 of the Appendix outlines the procedure used to calculate standard errors.

6 Estimation Results and Policy Experiments

Table 6 presents two sets of estimation results for a simplified version of the model in which there is no heterogeneity in the migration parameters, μ_η, σ_η, μ_λ, and λ_b. The first column presents estimates when the Census-derived weights are used, while the second column presents estimates when the MMP-provided weights are used. In both sets of estimates, the mean of the location utility shock while in the United States is found to be negative, in line with the expectation that individuals prefer to reside in Mexico. In both specifications, border enforcement is found to have a statistically and economically significant effect on the cost of migration. Using the Census-derived weights, the point estimate of 0.72 for λ_b suggests that a 10% increase in the Border Patrol Payroll leads to a 7.2% increase in the cost of migration. This, together with the estimate of 0.64 for μ_λ implies that the cost of migration grew from about $4,000 in 1987 to about $8,900 by the year 2000. The estimates derived using the MMP-provided weights suggest that border enforcement had a much smaller impact on the cost of migration, as the cost of migration increased from about \$3,700 in 1987 to \$5,800 in 2000. The estimates in Table 6 highlight the importance of re-weighting the MMP data using information from the Census. Using the MMP-derived weights results in a larger mean disutility from residing in the U.S. (-3.13 v.s. -1.98), lower migration costs, and a smaller effect of border enforcement. These differences could follow from the reduced weight that the Census-based scheme places on communities where return migration is common and trip durations are short.

The primary estimation results are presented under specification I of Table 7. These columns present estimates of the migration parameters for two different types, along with the coefficients related to the mixing probability over types. Type 1 can be characterized as a high-migration, low-cost type that has been relatively unaffected by the escalation of border enforcement over the 1990s. Type 2, on the other hand, is a high cost type that experienced substantial cost increases due to the growth in border policing. Type 2 has a higher mean disutility to being in the U.S. (-1.92 v.s. -0.76). For Type 2 individuals, a 10% increase in the Border Patrol Payroll increases the cost of migration by 8%, suggesting that migration costs increased from about \$5,500 to well over \$10,000 by the end of the decade. However, Type 1 individuals did not experience an increase in migration costs. In fact, the point estimate of λ_b for this Type is negative (-0.21), although it is small in magnitude and imprecisely estimated. The estimates suggest that for Type 1, the cost of migration varied between about \$2,200 and \$1,800.

The estimates of the mixing probability coefficients suggest that the unconditional proportion of the sample that belongs to Type 1 is about 17%, so the majority of individuals belong to the high-cost migration type. Being the son of a migrant substantially increases one's probability of being the low-cost Type 1, in line with expectations. Individuals from urban areas, who exhibit lower migration rates, are less likely to be of Type 1, but this is imprecisely estimated. Similarly, there do not appear to be statistically significant differences in the Type probabilities for different education groups, suggesting that differences in the earnings distributions account for most of the difference in observed migration patterns across these groups. While I do not find that more educated individuals have lower migration costs, as suggested by Chiquiar and Hanson (2005), the model nevertheless reveals a mechanism driving intermediate selection that preserves this basic intuition. For a given cost of migration, individuals with lower levels of education have to wait longer in Mexico before they can save up the funds needed to migrate. As education increases and Mexican incomes rise, it becomes easier to finance migration, but the international wage gap is also shrinking, creating an intermediate pattern of selection on education. This mechanism depends on asset accumulation in the model, although it should be noted that a similar pattern of selection might also be produced by a model like that in Colussi (2006) if networks are stronger for individuals with intermediate levels of education.

6.1 Model Fit

To assess the fit of the model, Table 8 compares some selected moments from the data and those predicted by the model under the estimated parameters. The panels of Table 8 compare the empirical and simulated moments for different sub-populations. The moments include the mean values of the fraction of time spent in the U.S., δ_i, the rate of trips taken per year, τ_i, and the m_i^j variables, which indicate if an individual has migrated by age j. The m_i^j variables capture the age-migration profile, and thus reflect the probabilities that individuals will undertake a first migration at different ages. Across all of the sub-samples, the model does an excellent job of matching the fraction of time spent in the U.S. and the rate of trips take per year. The model matches the age-migration profile fairly well, although the model performs better along this dimension for some sub-populations than for others. In the complete sample, the model slightly over-predicts the fraction of individuals that have migrated by some ages. The model performs very well in matching the age-migration profile for the Urban Sample, but tends to over-predict migration for the Rural Sample. For both the 4-9 Years and > 9 Years Education groups, the model fits the age-migration profiles very well.

Return migration probabilities provide another dimension along which to assess the fit of the model. Table 9 reports the empirical and simulated probabilities that an individual returns to the U.S. after spending one, two, or three years abroad on a first migratory trip, and after spending one or two years abroad on a second trip.[17] These hazard rates can be calculated directly as transition probabilities in the model simulations. However, since we observe migration durations in months in the data, the reported hazards from the data are based on a discretization.[18] Considering all of the migrants in the complete sample, the model matches the hazard rate after year 1 of trip 1 quite well (0.33 for the model v.s. 0.36 in the data). However, the model over-predicts hazard rate for subsequent years of trip 1, and under-predicts the return hazard during trip 2. The performance of the model in matching these hazards improves if we look at the population whose fathers were not migrants. For this sub-population, which accounts for the vast majority of all transition observations in the data, the model provides a decent fit for the return probabilities after the first and second

[17] These rates are only reported if we observe a sample size of at least 15 for these transitions.

[18] For example, to calculate the return probability after the second year of a trip, I consider the individuals who have a completed trip duration greater than 12 months, or a censored trip duration greater than 24 months. The reported hazard in this case is the fraction of individuals in this group that had a completed duration greater than 12 months and less than or equal to 24 months.

years of the first trip. The model still over-predicts the return hazard for year 3 of trip 1, and under-predicts the hazard rates during the second trip. This suggests that the model may have trouble capturing all of the effects that a father's migration may have on altering an individual's trip duration.

Looking across the different sub-populations, the model tends to predict mildly increasing hazard rates for return over the course of a migratory trip. This appears to be driven by asset accumulation in the model, as individuals come closer to meeting endogenously determined savings targets the longer they stay in the United States. The data generally display decreasing, or approximately constant hazard rates through the first two years of a first migration.[19] However, if one looks at individuals who migrate for the first time by age 25, both the model and the data display an increasing hazard rate from the first to the second year of the first trip. This is noteworthy and provides some validation for the asset accumulation mechanism present in the model.

Overall, the model does a fairly good job of matching the return probabilities after the first and second year of a first trip, especially for those individuals whose fathers were not migrants (the vast majority of migrants in the sample). The model does less well in matching the hazards late in a first migration or during a second migration. However, we have far fewer observations for these transitions, so these are not very precisely estimated from the data. It is also hard to judge the model on the basis of fitting hazard rates because in the underlying data, we observe trip durations reported in months and not years. This creates a time-aggregation problem that makes it difficult to exactly compare the discretized hazard rates from the data with the hazard rates from the model. It may be much more informative to assess the fit of the model on the basis of moments that are less distorted by time aggregation, such as the fraction of time spent in the U.S., and the number of trips made per year. Based on the these moments, the model fits the data very well.

Finally, I also check on how well the model predicts the asset distribution for individuals at the end of the sample. I used MFLS data on individuals aged 25 or less to estimate the parameters of the initial distribution of assets. To assess the fit of the model, I compare the distribution of assets predicted by the model for individuals aged 25 or greater in 1999-2000 with the actual MFLS data for individuals aged 25-30 in 2002. A comparison of the distributions is offered in Table 5. Overall, the distributions match quite well, although the model tends to over-predict mass at low levels of assets and under-predict mass in the tail. This tends to be a common shortcoming of many models of wealth accumulation (Cagetti and Nardi, 2008).

[19] It is hard to investigate duration dependence for a second trip because the sample sizes here are quite small.

6.2 Endogeneity of Border Enforcement

The estimates of the effect of border enforcement on migration costs may be biased if border enforcement is endogenously determined in response to variables that alter the incentives to migrate. This possibility has been explored in a series of papers by Hanson and Spilimbergo (1999,2001). Hanson and Spilimbergo (2001) provide evidence that border enforcement is negatively correlated with prices in sectors that employ many illegal immigrants, suggesting that producers pressure policymakers to loosen border enforcement when demand is high. This would create a negative correlation between border enforcement and the incentives to migrate. On the other hand, Hanson and Spilimbergo (2001) also find that border enforcement increases in response to general labor market tightness, which would create a positive correlation between border enforcement and the incentives to migrate. It could also be the case that border enforcement responds to non-economic incentives to migrate, such as drug violence. Since the model doesn't account for these events, the parameter estimates presented above could be biased.

I address this concern in two ways. First, I replace the observed border enforcement series with a series that has been predicted using an instrumental variable, and I re-estimate the model using this predicted series. The instrumental variable that I use is real defense spending, one of the instruments used in Hanson and Spilimbergo (1999). In a first stage, I predict border enforcement using defense spending, a dummy for the Peso Crisis, and an interaction between the two variables. Section A.8 of the Appendix describes the first stage and compares the observed level of border enforcement with the predicted series. Defense spending is negatively correlated with border enforcement before 1995, reflecting a trade-off argument between resources for national and domestic defense (Hanson and Spilimbergo, 1999). However, defense spending is positively correlated with border enforcement after 1995, perhaps reflecting the fact that border policing came to be seen as more of a national security issue in the late 1990s. Relative to the observed series, the predicted series doesn't fluctuate as much before 1995, and doesn't rise as much in the late 1990s, which were boom years in the United States. The predicted series thus exhibits less variation that might be correlated with unobserved shocks to migration incentives. The structural parameter estimates using this predicted series are presented under specification II in Table 7. The parameter estimates are very similar to those in the first specification, suggesting that the initial estimates are not severely affected by endogeneity bias.

The second attempt to control for the endogeneity of border enforcement involves directly modeling some of the shocks that might be correlated with border enforcement and are currently omitted from the model. Specifically, I consider aggregate macro shocks in the United States. This might be important because one of the most credible scenarios for correlation between incentives to migrate and border enforcement unfolds in the late 1990s, when U.S. wages were quite high, and border enforcement grew rapidly. The estimates of the effect of border enforcement on cost could be biased downwards if individuals migrated in the late 1990s in response to higher wages despite higher border enforcement. To model this, I introduce a new state variable, S_t, which represents the state of the U.S. economy. S_t can take one of three values $\{1,2,3\}$, corresponding to Low, Medium, and High incomes states, respectively. I assume that S_t evolves according to a first-order Markov process, with π_{jk} denoting the probability of transitioning from state j to state k from between period t and $t+1$. The aggregate state enters the model by affecting income while in the U.S., so the U.S. income process now becomes:

$$\begin{aligned}\log(w_t^{US}) &= \gamma_0^{US} + \gamma_a^{US} Age_{it} + \sum_j \gamma_{e,j}^{US} EDU_{i,j} + \gamma_T^{US} Trend_t \\ &\quad + \gamma_{S1}^{US} 1(S_t = 1) + \gamma_{S2}^{US} 1(S_t = 2) + \varepsilon_{i,t}^{US} \qquad (20)\end{aligned}$$

Where $1(S_t = j)$ is an indicator function. I use the method developed by Tauchen (1986), and a series on lagged U.S. GDP growth to assign an aggregate state to each sample year from 1987 to 2000, and to estimate the transition probabilities π_{jk}. Section A.9 of the Appendix contains the details of this estimation procedure. The estimates suggest that 1990 and 1991 were Low state years, 1997-1999 were High state years, and the rest were Medium state years. The parameters γ_{S1}^{US} and γ_{S2}^{US} are estimated to be 0.18 and 0.22, respectively, suggesting that incomes are significantly higher during years that enter the Medium and High states. Adding the state variable S_t to the model means that S_t must be added to the information sets Ω_t^f and Ω_t^h. The structural parameter estimates using this version of the model are presented under specification III in Table 7. As before, the parameter estimates are very similar to those in the first specification, suggesting that the initial estimates are not severely affected by endogeneity bias.

These two alternate specifications suggest that transitory shocks to border enforcement do not play an important role in identifying the parameters related to the effect of border enforcement on the cost of migration. Rather, the effect of border enforcement is identified by the large escalation of border enforcement following the peso crisis and the changes in migration behavior that this induced across successive cohorts (recall that the moments include various measures of migration behavior across various cohorts as they enter the sample). Since the basic model already incorporates the major effects of the Peso Crisis, these cross-cohort comparisons can cleanly identify the effect of border enforcement on migration costs.

6.3 Policy Experiments

We are now in a position to perform policy experiments using my preferred parameter estimates from Specification I in Table 7. First, I consider the effect of changes in the level of border enforcement on migration behavior. To isolate the effect of border enforcement, the following counterfactuals are performed by considering a stationary environment in which mean incomes and the mean level of the real exchange rate do not follow trends over time, and instead are fixed to their year 2000 levels. In Table 11, I simulate the behavior of the individuals in my sample in response to different constant levels of the log of the Border Patrol payroll, which range from 0.5 to 2.3. (In the data, this variable varies approximately between 1 and 2). For different levels of border enforcement, I look at the response of migration rates, captured by the m_i^{19} and m_i^{23} variables, the fraction of time spent in the United States, δ, trips per year, τ, average durations for first and second trips, and the average expected lifetime utility in the sample (expressed as a percentage of the average utility under the first row counterfactual, assuming 5,000 pesos of initial wealth).

The results in Table 11 suggest that increasing the level of border enforcement clearly reduces migration rates, and the number of trips per year, by driving up migration costs. Average trip durations increase on both the first and second trips, as predicted by theory. However, the average fraction of time spent in the United States monotonically declines, suggesting that the deterrent effect of border enforcement outweighs the effect of increased durations. Thus, these counterfactuals do not support the proposition that tighter border enforcement increases the population of undocumented migrants. However, the simulations do reveal the limits of a strategy of border enforcement escalation. Notice that after the level of border enforcement reaches 1.9, continued increases do very little to change migration behavior. This is because at these levels, all of the high-cost Type 2 individuals have been deterred from migrating, but the high levels of enforcement do not stop the low cost Type 1 individuals from migrating. Border enforcement escalation might not backfire, but it appears to be ineffective at producing continual reductions in illegal migration. The simulations also suggest that the utility costs of enforcement escalation may be substantial for potential migrants. Average expected lifetime utility declines by about 6% moving from the lowest to the highest level of border enforcement considered here.

In Table 12, I consider what would have happened if the U.S. had not responded to the Peso Crisis with a large escalation in border enforcement. That is, I return to the non-stationary setting of the estimated model, and consider a counter-factual in which the intensity of border enforcement is stuck at the 1994 level for all years after 1994. The results suggest that without the escalation, migration rates would have been substantially higher. Migration durations would have been lower, but the overall fraction of time spent in the U.S.

would have risen by about 20% from 0.15 to 0.18.

It is useful to compare the results on border enforcement to those obtained by Angelucci (2005). Using a much different set of cohorts in the MMP data observed over the years 1972-1993, Angelucci finds that an approximate 50% increase in border enforcement intensity results in the reduction of illegal immigration by about one third (p.26). However, such an increase in enforcement would also steeply reduce return migration probabilities, so that these forces roughly offset in determining the stock of illegal immigrants in the U.S. at any given time (p. 34-35). In the Table 11, I find a greater deterrent effect, with an approximate 50% increase in the log payroll from 0.9 to 1.5 causing about a 50% reduction in extensive migration rates (m_i^{23}), and the fraction of time spent in the United States. Indeed, I find that the deterrent effect is sufficiently strong that increased border enforcement reduces the total amount of time that individuals spend abroad. The differences between these results and those in Angelucci (2005) may be due to the substantial differences in the samples and time periods used across our studies. Hanson and Spilimbergo (1999) do find that higher levels of border enforcement increase the number of apprehensions at the border, which suggests that enforcement activities are productive in increasing the difficulty of a border crossing. However, it is difficult to make sharp comparisons with the results since Hanson and Spilimbergo (1999) do not look at the effects of border enforcement on completed migration behavior. The link between apprehension data and migration rates is difficult to assess, since individuals might be apprehended multiple times before crossing the border.

In Table 13, I turn to the effect of changes in the real exchange rate. Theoretically, the migration response to exchange rate fluctuations is complex and ambiguous. By increasing the value of foreign earnings, an increase in the real exchange rate both encourages more migration but may also reduce trip durations if individuals are able to more quickly meet endogenous savings targets. Furthermore, in the case of Mexico-U.S. migration, where we believe that migration costs are denominated in dollars, an increase in the exchange rate also increases the cost of migration. To isolate the effect of a change in the exchange rate, I again consider a stationary environment with mean income fixed to its year 2000 levels and border enforcement set to the 1995 level. As table 13 demonstrates, increasing the real exchange rate from 5 to 14 results in a monotonic decline in migration rates and time spent abroad, reflecting the increase in migration costs. However, exchange rate increases also reduce trip durations, since foreign earnings are now worth more and allow individuals to more quickly reach savings targets. This contrasts sharply with the increases in trip durations that occur when migration costs are directly increased. Interestingly, while increasing the exchange rate from 5 to 14 has a large negative effect on migration rates, it has a very small effect on average lifetime utility, unlike an increase in migration costs. While those who are prevented from migrating lose out, those who do migrate gain because of the increased value of foreign earnings. To highlight this point, I consider another set of counterfactuals in Table 14, where I repeat the exchange rate experiments but hold the peso cost of migration fixed. In these experiments, increasing the exchange rate leads to more migration and substantially shorter trip durations. Lifetime utility increases by about 4% moving from an exchange rate of 5 to a rate of 14.

The results here highlight the powerful effect that exchange rate fluctuations can have on patterns of circular migration. Migration decisions and trip durations appear to be very sensitive to exchange rate fluctuations. These results highlight a mechanism unique to models with asset accumulation. In a migration model without asset accumulation, exchange rate fluctuations (holding relative prices constant) only affect migration costs, since individuals consume all of their contemporaneous earnings. Dollars would never be exchanged for pesos for the purpose of consumption in such models. However, when we allow for asset accumulation, exchange rate fluctuations also alter return migration incentives, as higher exchange rates increase the value of foreign earnings in the home country.

7 Conclusion

This paper has developed a model of repeated circular migration with asset accumulation which was estimated using data on young men from the Mexican Migrant Project over the period 1987-2000. The empirical model accounts for important changes in the macro environment that shaped the incentives to migrate over the course of the 1990s, including the effects of the Peso Crisis, and the rapid escalation of border enforcement. Estimates suggest that there is a positive and economically significant relationship between border enforcement and the cost of migration, at least for a subset of the population.

Counterfactual experiments do not support the hypothesis that border enforcement might backfire and increase the population of illegal immigration by increasing trip durations. Indeed, I find that the deterrent effect of more stringent border enforcement outweighs the positive effect on trip durations. However, some individuals are found to be high-migration types that are insensitive to continued enforcement escalation. This suggests that ongoing enforcement growth may have limited effects on migration behavior. Counterfactual experiments also suggest that migration behavior is sensitive to exchange rates fluctuations, as they alter both the costs of migration and the peso value of earnings in the United States.

The limitations of the model estimated here suggest natural avenues for future research. I have not considered the general equilibrium effects of changes in border enforcement or exchange rates. It would be interesting to estimate a model in which incomes in the U.S.

and Mexico are endogenous, as changes in border enforcement may also have an impact on wages on both sides of the border. Additionally, although I have treated education as an exogenous variable, it would be interesting to endogenize the education decision. This could have implications for the consequences of border enforcement policy. For example, tighter border enforcement might cause some individuals to invest more in education (instead of migration). This could offset some of the utility losses associated with higher migration costs.

References

Angelucci, Manuela, "U.S. Border Enforcement and the Net Flow of Mexican Illegal Migration," 2005. IZA Discussion Paper 1642.

Bellemare, Charles, "A life-cycle model of outmigration and economic assimilation of immigrants in Germany," *The European Economic Review*, 2007, *51*, 553576.

Berninghaus, Siegfried and Hans Gunther Seifert-Vogt, "The role of the target saving motive in guest worker migration: A theoretical study," *The Journal of Economic Dynamics and Control*, 1993, *17*, 181–205.

Borjas, George J., "Self-Selection and the Earnings of Immigrants," *The American Economic Review*, September 1987, *77* (4), 531–553.

_ **and Lawrence F. Katz**, "Evolution of the Mexican-Born Workforce in the United States," in "Mexican Immigration to the United States," National Bureau of Economic Research, 2007, pp. 13–56.

Cagetti, Marco and Mariacristina De Nardi, "Wealth and Inequality: Data and Models," *Macroeconomic Dyanamics*, 2008, *12*, 285–313.

Carrion-Flores, Carmen E., "What Makes You Go Back Home? Determinants of the Duration of Migration of Mexican Immigrants in the United States," 2006. Unpublished Working Paper.

Chiquiar, Daniel and Gordon H. Hanson, "International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States," *The Journal of Political Economy*, 2005, *113* (2), 239–281.

Colussi, Aldo, "Migrants' Networks: An Estimable Model of Illegal Mexican Migration," January 2006. Unpublished Working Paper.

Djajic, Slobodan and Ross Milbourne, "A General Equilibrium Model of Guest-Worker Migration," *Journal of International Economics*, 1988, *25*, 335–351.

Donato, Katherine M., Jorge Durand, and Douglas S. Massey, "Stemming The Tide? Assessing the Deterrent Effects of the Immigration Reform and Control Act," *Demography*, 1992, *29* (2), 139–157.

Dustmann, Christian and Oliver Kirchkamp, "The optimal migration duration and activity choice after re-migration," *Journal of Development Economics*, 2002, *67*, 351372.

_ **and Yoram Weiss**, "Return Migration: Theory and Empirical Evidence from the UK," *British Journal of Industrial Relations*, June 2007, *45* (2), 236256.

Gathmann, Christina, "Effects of enforcement on illegal markets: Evidence from migrant smuggling along the southwestern border," *Journal of Public Economics*, 2008, *92*, 1926–1941.

Gourinchas, Pierre-Olivier and Jonathan A. Parker, "Consumption Over the Life-Cycle," *Econometrica*, 2002, *70* (1), 47–89.

Hanson, Gordon H., "Illegal Migration from Mexico to the United States," *Journal of Economic Literature*, 2006, *44* (4), 869 – 924.

_ **and Antonio Spilimbergo**, "Illegal Immigration, Border Enforcement, and Relative Wages: Evidence from Apprehensions at the US-Mexico Border," *The American Economic Review*, 1999, *89* (5), 1337 – 1357.

_ **and** _ , "Political Economy, Sectoral Shocks, and Border Enforcement," *Canadian Journal of Economics*, 2001, *34* (3), 612 – 638.

Hill, John K., "Immigrant Decisions Concerning Duration of Stay and Migratory Frequency," *The Journal of Development Economics*, 1987, *25*, 221–234.

Ibarraran, Pablo and Darren Lubotsky, "Mexican Immigration and Self-Selection: New Evidence from the 2000 Mexican Census," in "Mexican Immigration to the United States," National Bureau of Economic Research, 2007, pp. 159–192.

Kirdar, Murat, "An Estimable Dynamic Model of Asset Accumulation and Return Migration," 2004. Unpublished Working Paper.

Lacuesta, Aitor, "Emigration and Human Capital: Who Leaves, Who Comes Back, and What Difference Does it Make?," 2006. Banco De Espana Working Paper No. 0620.

Lindstrom, David P., "Economic Opportunity in Mexico and Return Migration from the United States," *Demography*, 1996, *33* (3), 357–374.

Massey, Douglas S. and Kristin E. Espinosa, "What's Driving Mexico-U.S. Migration? A Theoretical, Empirical, and Policy Analysis," *The American Journal of Sociology*, 1997, *102* (4), 939–999.

_ **, Jorge Durand, and Nolan J. Malone**, *Beyond Smoke and Mirrors: Mexican Immigration in an Era of Economic Integration*, Russell Sage Foundation Publications, 2003.

McKenzie, David and Hillel Rapoport, "Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico," *The Journal of Development Economics*, 2007, *84*, 1–24.

Mesnard, Alice, "Temporary migration and capital market imperfections," *Oxford Economic Papers*, 2004, *56*, 242–262.

Moraga, Jesus Fernandez-Huertas, "New Evidence on Emigrant Selection.," November 13 2006. Unpublished Dissertation: Columbia University.

Newey, Whitney K. and Daniel McFadden, "Large Sample Estimation and Hypothesis Testing," *Handbook of Econometrics, Volume IV*, 1994, pp. 2113–2245.

Orrenius, Pia M. and Madeline Zavodny, "Self-selection among undocumented immigrants from Mexico," *The Journal of Development Economics*, 2005, *78*, 215–240.

Passel, Jeffrey S., "Estimates of the Size and Characteristics of the Undocumented Population," March 21 2005. Pew Hispanic Center Report.

Piore, Michael J., *Birds of passage: migrant labor and industrial societies*, Cambridge University Press, 1979.

Rendon, Silvio and Alfredo Cuecuecha, "International Job Search: Mexicans in and out of the US," 2007. IZA Discussion Paper No. 3219.

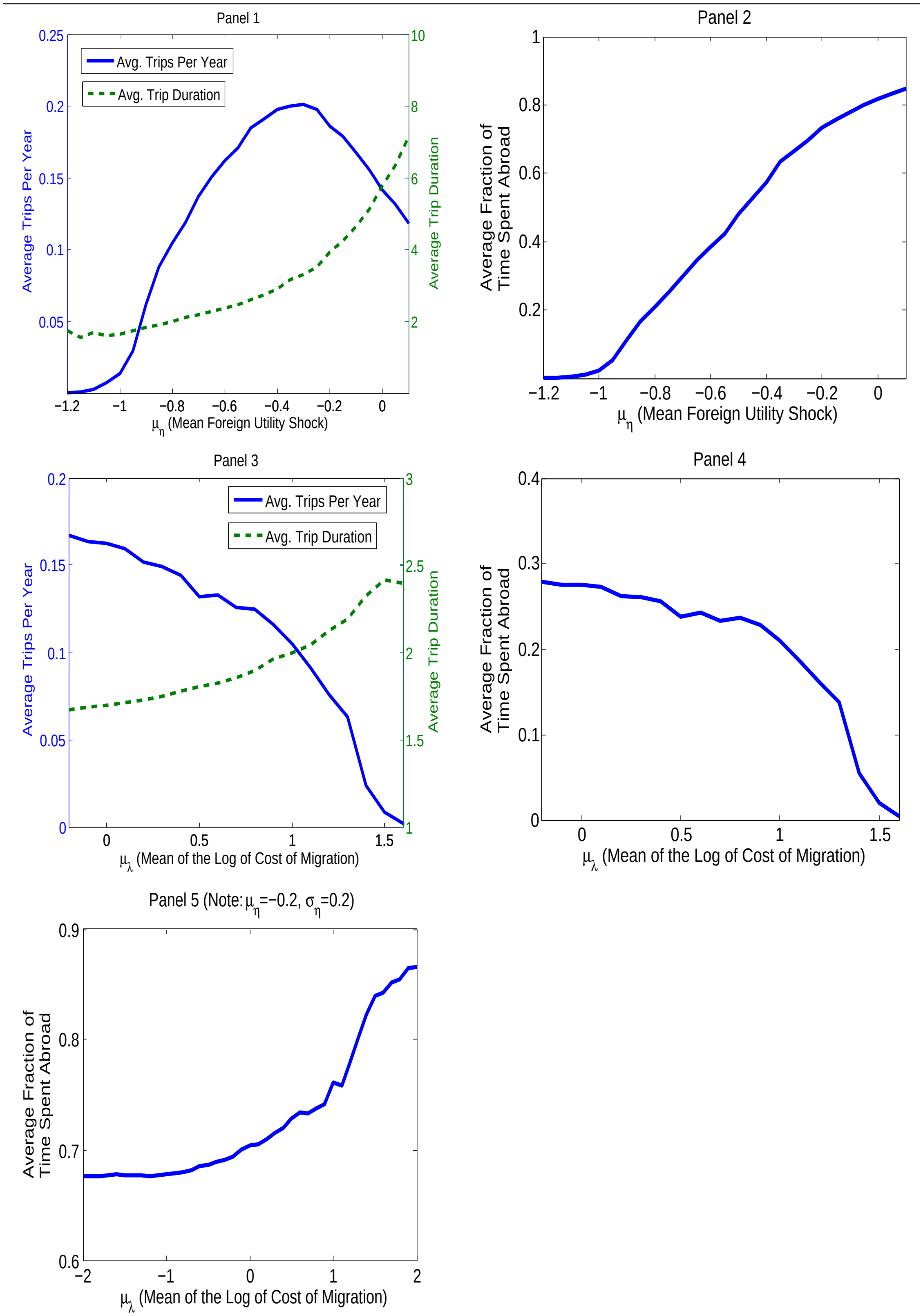
Reyes, Belinda I., "Changes in trip duration for Mexican immigrants to the United States," *Population Research and Policy Review*, 2004, *23*, 235257.

_ **and Laura Mameesh**, "Why Does Immigrant Trip Duration Vary Across U.S. Destinations?," *Social Science Quarterly*, June 2002, *83* (2), 580–593.

Tauchen, George, "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions," *Economics Letters*, 1986, *20*, 177–181.

Yang, Dean, "Why Do Migrants Return to Poor Countries? Evidence from Philippine Migrants' Responses to Exchange Rate Shocks," *The Review of Economics and Statistics*, 2006, *88*, 715–735.

Figure 1: The Effect of μ_η and μ_λ on the Number of Trips and Time Spent Abroad



Each point on a graph represents averages taken with respect to 1000 simulated life histories for an individual with $T = 50$ observed for T periods. For all panels, unless otherwise noted, $\sigma_\eta = 0.5$, $\mu_h = 2$, $\sigma_h = 0.25$, $\mu_f = 2.5$, $\sigma_f = 0.25$, $\mu_e = 0.5$, $\sigma_e = 0.05$, $\sigma_\lambda = 0.1$, $\beta = .96$, $ppp = 1$, $R = 1.01$. For Panels 1 and 2, $\mu_\lambda = 1$. For Panels 3 and 4, $\mu_\eta = -0.8$.

Table 1: Descriptive Statistics: Individual Characteristics

Variable	Mean	Variable	Mean
Education:		**Year Born:**	
0-3 Years	0.07	1960-1964	0.01
4-6 Years	0.30	1965-1969	0.09
7-9 Years	0.38	1970-1974	0.52
10-12 Years	0.21	1975-1979	0.34
> 12 Years	0.04	1980-1984	0.04
Commun. Type:		**Other:**	
Rancho	0.34	Father Mig. (Initial)	0.08
Town	0.29	Property (Initial)	0.06
Smaller Urban	0.11	Years in Sample	9.77
Metro	0.25		

N=1401 for all variables. Means are weighted using the Census-derived sampling weights discussed in the text. The Father Mig. variable is a dummy indicating whether or not an individual's father had any U.S. migration experience before or during the first year of the individual's adulthood.

Table 2: Descriptive Statistics on Migration Experience

	Complete Sample			Migrants Only		
Variable	**Mean**	**St. Dev.**	**N**	**Mean**	**St. Dev.**	**N**
0 Trips	0.61	0.49	1401	0	0	382
1 Trip	0.29	0.45	1401	0.73	0.44	382
2 or More Trips	0.10	0.30	1401	0.27	0.44	382
m_i^{15}	0.02	0.15	673	0.05	0.22	217
m_i^{17}	0.10	0.30	1027	0.23	0.42	306
m_i^{19}	0.17	0.37	1232	0.41	0.49	354
m_i^{21}	0.25	0.44	1250	0.64	0.48	353
m_i^{23}	0.31	0.46	1113	0.79	0.41	322
m_i^{25}	0.31	0.46	861	0.83	0.38	250
δ_i **(% of time in U.S.)**	0.15	0.25	1401	0.38	0.28	382
τ_i **(trips per year)**	0.06	0.10	1401	0.15	0.11	382
Duration	-	-		23.72	23.32	432
Duration (Trip 1)	-	-		28.44	26.04	281

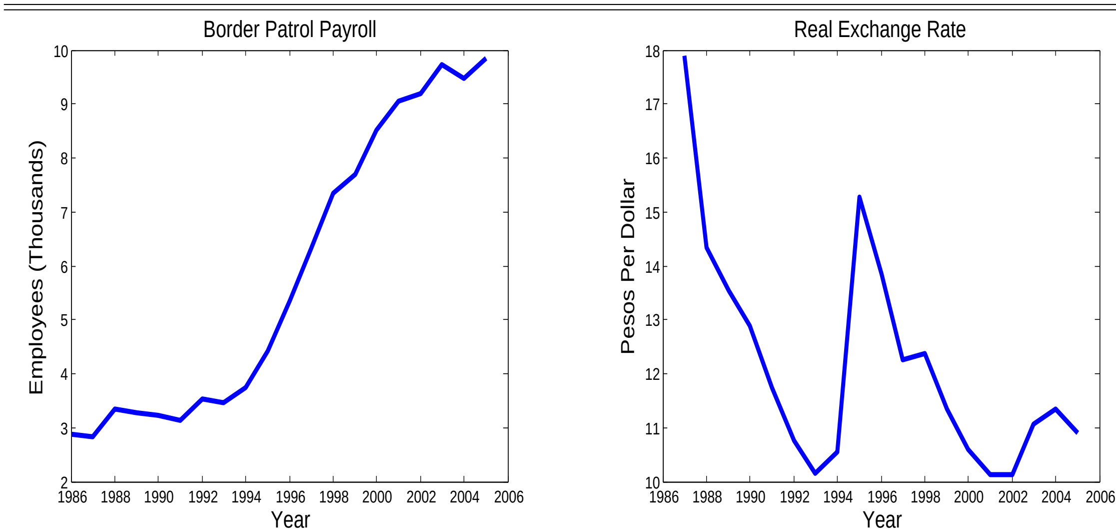
Means are weighted using the Census-derived sampling weights discussed in the text. The m_i^j variables take values of 1 if an individual has any migration experience by the end of age j and 0 otherwise. The δ_i variable measures the fraction of an individual's observed adult life (measured in months) spent in the United States. The τ_i variable measures the number of trips taken by an individual divided by the number of years an individual is observed in the sample.

Table 3: Variable Means By Education and Community Type

	Educ 0-3	Educ 4-9	Educ>9	Rural	Urban
0 Trips	0.71	0.58	0.66	0.54	0.73
1 Trip	0.27	0.31	0.23	0.33	0.21
2 or More Trips	0.02	0.11	0.11	0.13	0.06
m_i^{15}	0.01	0.02	0.04	0.03	0.01
m_i^{17}	0.05	0.12	0.03	0.11	0.08
m_i^{19}	0.09	0.19	0.10	0.19	0.12
m_i^{21}	0.18	0.27	0.25	0.30	0.17
m_i^{23}	0.19	0.34	0.27	0.34	0.26
m_i^{25}	0.14	0.33	0.29	0.33	0.27
δ_i **(% of time in U.S.)**	0.06	0.15	0.17	0.17	0.11
τ_i **(trips per year)**	0.03	0.06	0.06	0.07	0.04
Duration (Trip 1)	14.76	27.25	34.64	29.78	23.25

Means are weighted using the Census-derived sampling weights discussed in the text.. The m_i^j variables take values of 1 if an individual has any migration experience by the end of age j and 0 otherwise. The δ_i variable measures the fraction of an individual's observed adult life (measured in months) spent in the United States. The τ_i variable measures the number of trips taken by an individual divided by the number of years an individual is observed in the sample. The Trips variables are dummy variables indicating the associated levels of observed trips.

Figure 2: Border Enforcement and Exchange Rate Series



Border Patrol Data collected by the Transactional Records Access Clearinghouse of Syracuse University. The Real Exchange Rate series is computed using exchange rate and CPI data taken from the IMF's International Financial Statistics database.

Table 4: US and Mexican Labor Income Distributions

	$log(w^{Mex})$	$log(w^{US})$
Constant	1.363***	3.006***
	(0.065)	(0.124)
Age	0.075***	-0.011***
	(0.002)	(0.003)
AgeSqr	-0.001***	
	(0.000)	
Education: 4-6 Years	0.276***	0.105
	(0.013)	(0.065)
Education: 7-9 Years	0.446***	0.140*
	(0.013)	(0.076)
Education: 10-12 Years	0.653***	0.143
	(0.018)	(0.089)
Education: More than 12 Years	1.166***	0.138
	(0.018)	(0.106)
Urban	0.357***	
	(.010)	
Time Trend	0.008	-0.004
	(0.007)	(0.006)
Crash	-0.611***	
	(0.065)	
TimeTrend*Crash	0.023***	
	(0.008)	
σ	0.541***	0.534***
	(0.000)	(0.002)
N	35,085	1,350

*Note: Stars Signify the following: *** significant at the 0.01 level, ** significant at the .05 level, * significant at the 0.1 level. Standard Errors are reported in parentheses. All estimates have been derived using a Method of Moments estimator. Labor income is measured in thousands of units of real pesos or dollars. The dependent variable is the log of twelve times an observed monthly income, since estimation of the structural model proceeds taking a year as the length of a period. Nominal wages are deflated using the Mexican and U.S. CPI series from the June 2010 release of the IMF's International Financial Statistics with 2000 as the base year.*

Table 5: Asset Distribution Parameter Estimates

Constant	0.459
	(1.126)
Age	-0.129**
	(0.050)
Educ>= 10	-0.513***
	(0.162)
Owns Property	-1.822***
	(0.133)
N	508

*Note: Stars Signify the following: *** significant at the 0.01 level, ** significant at the .05 level, * significant at the 0.1 level. Standard Errors are reported in parentheses. All estimates have been derived using a Method of Moments estimator. Assets measured in thousands of real pesos. Nominal assets are deflated using the Mexican CPI series from the June 2010 release of the IMF's International Financial Statistics with 2000 as the base year.*

Table 6: Estimation Results - One Type

Specification:	I	II
μ_η	-1.98***	-3.13***
	(0.34)	(0.52)
$\log \sigma_\eta$	0.02	1.11***
	(0.05)	(0.36)
μ_λ	0.64**	0.88*
	(0.28)	(0.47)
λ_b	0.72***	0.41*
	(0.13)	(0.23)
Sampling Weight	Census	MMP

*Note: Stars Signify the following: *** significant at the 0.01 level, ** significant at the .05 level, * significant at the 0.1 level. Standard Errors are reported in parentheses.*

Table 7: Estimation Results - Two Types

	I		II		III	
	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
Migration Params.:						
μ_η	-0.764	-1.920***	-0.775	-1.879**	-0.793	-1.759**
	(1.988)	(0.184)	(1.38)	(0.754)	(0.769)	(0.736)
$\log \sigma_\eta$	0.839	0.827***	0.826	0.800	0.865	0.858
	(1.416)	(0.299)	(4.865)	(1.035)	(1.312)	(0.750)
μ_λ	1.040**	0.866***	1.024***	0.874**	1.051	0.869
	(0.439)	(0.181)	(0.099)	(0.441)	(0.855)	(2.583)
λ_b	-0.215	0.796***	-0.222	0.805****	-0.223	0.793
	(0.341)	(0.035)	(0.211)	(0.305)	(0.576)	(1.955)
Mixing Params.:						
Constant	0.689		0.698		0.809	
	(2.446)		(1.785)		(3.112)	
Urban	-1.293		-1.211		-1.387	
	(2.153)		(1.928)		(3.250)	
Father Migrated	2.244**		2.215*		2.257	
	(1.017)		(1.202)		(1.422)	
Educ 4-9 Years	-2.466		-2.493		-2.543	
	(2.536)		(1.780)		(4.148)	
Educ $\geq$ 10 Years	-2.540		-2.528		-2.747	
	(2.887)		(2.528)		(3.438)	
Predict B_t	No	No	Yes	Yes	No	No
U.S. Macro Shocks	No	No	No	No	Yes	Yes

*Note: Stars Signify the following: *** significant at the 0.01 level, ** significant at the .05 level, * significant at the 0.1 level. Standard Errors are reported in parentheses.*

Table 8: Comparison of Empirical and Simulated Moments

	Complete Sample			YearAdult>1990			Urban Sample	
	Empirical	Simulated		Empirical	Simulated		Empirical	Simulated
m_i^{17}	0.10	0.09	m_i^{17}	0.11	0.09	m_i^{17}	0.08	0.06
m_i^{19}	0.17	0.21	m_i^{19}	0.17	0.17	m_i^{19}	0.12	0.15
m_i^{21}	0.25	0.29	m_i^{21}	0.20	0.19	m_i^{21}	0.17	0.22
m_i^{23}	0.31	0.32	m_i^{23}	0.25	0.20	m_i^{23}	0.26	0.25
m_i^{25}	0.31	0.35	m_i^{25}	0.22	0.21	m_i^{25}	0.27	0.28
δ_i	0.15	0.15	δ_i	0.12	0.11	δ_i	0.11	0.10
τ_i	0.06	0.07	τ_i	0.06	0.05	τ_i	0.04	0.04

	Rural Sample			Educ. 4-9 Years			Educ. > 9 Years	
	Empirical	Simulated		Empirical	Simulated		Empirical	Simulated
m_i^{17}	0.11	0.10	m_i^{17}	0.12	0.09	m_i^{17}	0.03	0.03
m_i^{19}	0.19	0.24	m_i^{19}	0.19	0.20	m_i^{19}	0.10	0.14
m_i^{21}	0.30	0.32	m_i^{21}	0.27	0.28	m_i^{21}	0.25	0.21
m_i^{23}	0.34	0.37	m_i^{23}	0.34	0.31	m_i^{23}	0.27	0.28
m_i^{25}	0.33	0.40	m_i^{25}	0.33	0.35	m_i^{25}	0.29	0.31
δ_i	0.17	0.18	δ_i	0.15	0.14	δ_i	0.17	0.14
τ_i	0.07	0.08	τ_i	0.06	0.06	τ_i	0.06	0.06

The m_i^j variables take values of 1 if an individual has any migration experience by the end of the j^{th} year of adulthood and 0 otherwise. The δ_i variable measures the fraction of an individual's observed adult life (measured in months) spent in the United States. The τ_i variable measures the number of trips taken by an individual divided by the number of years an individual is observed in the sample. The tables report the mean values of these variables in the empirically observed sample and in a simulated sample generated as part of the estimation procedure.

Table 9: Empirical and Simulated Return Migration Probabilities

	Complete Sample				Father Not Mig.				Father Mig.		
	Empirical	Simulated	N		Empirical	Simulated	N		Empirical	Simulated	N
Trip1:				Trip1:				Trip1:			
Year 1	0.36	0.33	358	Year 1	0.33	0.32	316	Year 1	0.47	0.34	42
Year 2	0.27	0.36	185	Year 2	0.30	0.36	169	Year 2	0.06	0.38	16
Year 3	0.23	0.40	108	Year 3	0.24	0.40	97	Year 3			
Trip2:				Trip2:				Trip2:			
Year 1	0.46	0.35	97	Year 1	0.42	0.34	84	Year 1			
Year 2	0.40	0.39	36	Year 2	0.45	0.39	33	Year 2			

	Urban, Father Not Mig.				Rural, Father Not Mig.				$m_i^{25} = 1$, Father Not Mig.		
	Empirical	Simulated	N		Empirical	Simulated	N		Empirical	Simulated	N
Trip1:				Trip1:				Trip1:			
Year 1	0.33	0.35	129	Year 1	0.34	0.31	187	Year 1	0.31	0.33	184
Year 2	0.22	0.39	64	Year 2	0.33	0.35	105	Year 2	0.36	0.36	106
Year 3	0.13	0.43	40	Year 3	0.29	0.38	57	Year 3	0.15	0.40	61
Trip2:				Trip2:				Trip2:			
Year 1	0.47	0.35	36	Year 1	0.41	0.34	48	Year 1	0.47	0.34	61
Year 2				Year 2	0.42	0.38	21	Year 2	0.44	0.39	27

The m_i^j variables take values of 1 if an individual has any migration experience by the end of the j^{th} year of adulthood and 0 otherwise. The δ_i variable measures the fraction of an individual's observed adult life (measured in months) spent in the United States. The τ_i variable measures the number of trips taken by an individual divided by the number of years an individual is observed in the sample. The tables report the mean values of these variables in the empirically observed sample and in a simulated sample generated as part of the estimation procedure.

Table 10: Distribution of Assets, Ages 25-30, at End of Sample

Bin:	Model	Data
$0 \leq A_t \leq 5$	0.19	0.14
$5 < A_t \leq 10$	0.11	0.11
$10 < A_t \leq 25$	0.24	0.16
$25 < A_t \leq 50$	0.17	0.16
$50 < A_t \leq 75$	0.05	0.09
$75 < A_t$	0.24	0.34

Table 11: Counterfactuals: Border Patrol Payroll

$\log B_t$	m^{19}	m^{23}	δ	τ	Dur. Trip 1	Dur. Trip 2	Exp. Utility
0.5	0.56	0.91	0.38	0.20	2.17	1.90	100
0.7	0.45	0.85	0.35	0.18	2.17	1.90	99
0.9	0.35	0.77	0.32	0.16	2.18	1.91	98
1.1	0.27	0.65	0.28	0.14	2.20	1.93	97
1.3	0.22	0.50	0.23	0.11	2.23	1.97	96
1.5	0.19	0.34	0.17	0.08	2.28	2.04	95
1.7	0.17	0.21	0.12	0.06	2.43	2.12	94
1.9	0.17	0.18	0.11	0.05	2.53	2.16	94
2.1	0.17	0.16	0.11	0.05	2.57	2.17	94
2.3	0.17	0.16	0.10	0.05	2.57	2.17	94

Table 12: Counterfactuals: Response to Peso Crisis

	Baseline	No Border Response
m^{17}	0.21	0.21
m^{23}	0.32	0.38
δ	0.15	0.18
τ	0.07	0.09
Dur. 1	2.55	2.23
Dur. 2	2.19	2.03

Table 13: Counterfactuals: Real Exchange Rate

ex_t	m^{19}	m^{23}	δ	τ	Dur. Trip 1	Dur. Trip 2	Exp. Utility
5	0.45	0.74	0.36	0.16	2.55	2.14	100
6	0.37	0.68	0.32	0.14	2.49	2.12	100
7	0.30	0.59	0.28	0.13	2.43	2.09	100
8	0.25	0.51	0.24	0.11	2.38	2.06	99
9	0.22	0.44	0.21	0.10	2.33	2.05	99
10	0.20	0.38	0.19	0.09	2.30	2.03	99
11	0.18	0.33	0.17	0.08	2.26	2.02	99
12	0.17	0.29	0.15	0.07	2.24	2.01	99
13	0.15	0.23	0.13	0.06	2.24	2.00	99
14	0.15	0.22	0.12	0.06	2.24	1.98	98

Table 14: Counterfactuals: Real Exchange Rate (Migration Costs Constant)

ex_t	m^{17}	m^{25}	δ	τ	Dur. Trip 1	Dur. Trip 2	Exp. Utility
5	0.13	0.17	0.10	0.04	3.24	2.39	100
6	0.14	0.19	0.10	0.04	3.00	2.31	100
7	0.14	0.21	0.12	0.05	2.77	2.24	100
8	0.15	0.26	0.13	0.06	2.57	2.15	101
9	0.15	0.30	0.15	0.07	2.42	2.07	101
10	0.16	0.35	0.17	0.08	2.31	2.01	102
11	0.16	0.39	0.18	0.09	2.23	1.96	102
12	0.17	0.42	0.19	0.10	2.17	1.92	103
13	0.17	0.45	0.20	0.10	2.12	1.89	103
14	0.17	0.47	0.21	0.11	2.08	1.86	104

A Appendix (Not for Publication)

A.1 Discrete Approximations of Expected Values

In order to numerically evaluate the value functions defined in Equations 4, 5, 8, and 9, one needs to compute the expectation of terms that depend on multiple random variables. For example, computation of the value function in Equation 4 requires the evaluation of the expression $E_{\Omega^h_{t+1}}\left[V^h_{t+1}(k_{t+1}|\Omega^h_{t+1})\right]$, where $\Omega^h_{t+1} = \{w^h_{t+1}, \lambda_{t+1}, ex_{t+1}\}$. Since each of the random variables in Ω^h_{t+1} are independently distributed, we can write this expectation as:

$$\begin{aligned} E_{\Omega^h_{t+1}}\left[V^h_{t+1}(k^h_{t+1}|\Omega^h_{t+1})\right] \;\; = \;\; & \int_0^\infty \int_0^\infty \int_0^\infty \Big[V^h_{t+1}(k^h_{t+1}|\{w^h_{t+1}, \lambda_{t+1}, ex_{t+1}\})* \\ & f_{w^h}(w^h_{t+1}) f_\lambda(\lambda_{t+1}) f_{ex_{t+1}}(ex_{t+1})\Big]\, dw^h_{t+1} d\lambda_{t+1} dex_{t+1} \qquad \text{(A-1)} \end{aligned}$$

Where $f_x(\cdot)$ represents the p.d.f. of the random variable x. Since direct evaluation of the multiple integrals in an expression like the one in Equation A-1 is computationally expensive, we approximate these expectations by replacing the continuous distributions of the random variables in the sets Ω^h_{t+1} and Ω^f_{t+1} with discrete approximations.

Consider an arbitrary random variable x with support over the range (-∞,∞) and c.d.f $F_x(\cdot)$. Let $\mathfrak{N}$ be a vector of $n+1$ equally spaced values on the interval $[0,1]$: $\mathfrak{N} = [0, \frac{1}{n}, \frac{2}{n}, ... \frac{n-1}{n}, 1]$. For each element of this vector, $\mathfrak{N}_i$, define a corresponding value $x_i^{-1} = F_x^{-1}(\mathfrak{N}_i)$, where $F_x^{-1}(\cdot)$ is the inverse of the c.d.f of x. Sequential pairs of the x_i^{-1} values divide the support of the variable x into n intervals, each having the same probability mass. For each interval, define:

$$\chi_i = \frac{\int_{x_i^{-1}}^{x_{i+1}^{-1}} x f_x(x) dx}{F_x(x_{i+1}^{-1}) - F_x(x_i^{-1})} \qquad \text{(A-2)}$$

The χ_i values give the expected value of x over n equally probable intervals, and thus serve as a set of approximating nodes. The expected value of x can be approximated as:

$$\int_{-\infty}^{\infty} x f_x(x) dx \approx \frac{1}{n}\sum_{i=1}^{n} \chi_i \qquad \text{(A-3)}$$

Returning to the example in A-1, let $\widetilde{w^h_{t,i}}$, $\widetilde{\lambda_{t,j}}$, and $\widetilde{ex_{t,k}}$ refer to the i^{th},j^{th}, and k^{th} approximating nodes of the distributions of these random variables for period t, where these nodes have been constructed in the same way that the χ_i nodes were constructed above for

x. Then $E_{\Omega^h_{t+1}}\left[V^h_{t+1}(k_{t+1}|\Omega^h_{t+1})\right]$ may be approximated as:

$$E_{\Omega^h_{t+1}}\left[V^h_{t+1}(k_{t+1}|\Omega^h_{t+1})\right] \approx \frac{1}{n^3}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} V^h_{t+1}(k_{t+1}|\{\widetilde{w^h_{t,i}}, \widetilde{\lambda_{t,j}}, \widetilde{ex_{t,k}}\}) \tag{A-4}$$

All expectations for the numerical solutions in this paper are approximated using analogous procedures.

A.2 Value Function Approximation Methods

A complete solution to the model presented here requires solving or approximating the value functions $\nu^{hh}_t(k_t|\Omega^h_t)$, $\nu^{hf}_t(k_t|\Omega^h_t)$, $\nu^{fh}_t(k_t|\Omega^f_t)$ and $\nu^{ff}_t(k_t|\Omega^f_t)$ for each t. This may be accomplished using approximations of two value functions for each t that can be used to approximate all of the others. First, Let ω_t represents the total wealth that a worker in the model has on hand. This includes the asset stock, k_t, adjusted for any wages or migration costs that the individual may have earned or paid at the start of that period. Next let us define the value function $\mathfrak{v}^h_t(\omega_t)$ as follows:

$$\begin{aligned} \mathfrak{v}^h_t(\omega_t) \;\; &= \;\; \max_{\mathcal{C}_{h,t}} \log(\mathcal{C}_{h,t}) + \beta E_{\Omega^h_{t+1}}\left[V^h_{t+1}(k_{t+1}|\Omega^h_{t+1})\right] \\ & \quad\;\; s.t.\;\; k_{t+1} = R[\omega_t - \mathcal{C}_{h,t}] \\ & \quad\;\; \mathcal{C}_{h,t} \le \omega_t \end{aligned} \tag{A-5}$$

Note that $\nu^{hh}_t(k_t|\Omega^h_t) = \mathfrak{v}^h_t(k_t + w^h_t)$, and that $\nu^{fh}_t(k_t|\Omega^h_t) = E_{w^h_t}\left[\mathfrak{v}^h_t(k_t + w^h_t)\right]$. Therefore, one only needs to approximate the value function $\mathfrak{v}^h_t(\omega_t)$ in order to approximate $\nu^{hh}_t(k_t|\Omega^h_t)$ and $\nu^{fh}_t(k_t|\Omega^h_t)$.

Suppose that we can evaluate $E_{\Omega^h_{t+1}}\left[\beta V^h_{t+1}(k^h_{t+1}|\Omega^h_{t+1})\right]$, either because this term can be easily computed (as when $t = T$), or because we have an approximation of this function. One could then follow conventional interpolation methods by first specifying an exogenous vector of n interpolation nodes $\overrightarrow{\omega} = [\omega^1, \omega^2, ...\omega^i, ...\omega^n]$. Next, for each node in $\overrightarrow{\omega}$, we could set $\omega_t = \omega^i$ and solve the problem defined in Equation A-5 using some numerical optimization algorithm. Doing this for every node in $\overrightarrow{\omega}$ would generate a vector of corresponding values, $\overrightarrow{\mathfrak{v}^h}$. Standard interpolation methods then permit the approximation of $\mathfrak{v}^h_t(\omega_t)$ from $\overrightarrow{\omega}$ and $\overrightarrow{\mathfrak{v}^h}$. Similarly, one can approximate a consumption function, $\mathcal{C}^*_{h,t}(\omega_t)$ based on the optimal consumption choices at the nodes $\overrightarrow{\omega}$.

One of the drawbacks of the conventional method is that any numerical optimization algorithm will typically require many function evaluations to solve the problem in Equation A-5 for each interpolation node. To lessen the computational burden, the optimal consumption choice $\mathcal{C}^*_{h,t}$ is approximated by constructing a a grid of 20 equally spaced candidate consumption levels spanning the interval $(0, \omega_t]$ and then selecting the candidate that maximizes utility as the approximation for $\mathcal{C}^*_{h,t}$.

The value functions $\nu^{hf}_t(k_t|\Omega^h_t)$ and $\nu^{ff}_t(k_t|\Omega^h_t)$ can be approximated by first approximating the value function $\mathfrak{v}^f_t(\omega_t)$, defined as:

$$\begin{aligned} \mathfrak{v}^f_t(\omega_t) \quad &= \quad \max_{\mathcal{C}_{f,t}} \log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + \beta E_{\Omega^f_{t+1}}\left[V^f_{t+1}(k_{t+1}|\Omega^h_{t+1})\right] \\ &\quad\quad s.t.\ k_{t+1} = R[\omega_t - ex_t\mathcal{C}_{f,t}] \\ &\quad\quad\quad \mathcal{C}_{f,t} \leq \frac{\omega_t}{ex_t} \end{aligned} \tag{A-6}$$

Approximation of $\mathfrak{v}^f_t(\omega_t)$ is sufficient because $\nu^{hf}_t(k_t|\Omega^h_t) = E_{w^f_t,\eta_t}\left[\eta_t + \mathfrak{v}^f_t(k_t + ex_t(w^f_t - \lambda_t))\right]$ and $\nu^{ff}_t(k_t|\Omega^h_t) = \eta_t + \mathfrak{v}^f_t(k_t + w^f_t)$. However, we cannot apply exactly the same approximation method to this function as we did for $\mathfrak{v}^h_t(\omega_t)$ because in this case, the optimal level of consumption expenditure depends on ex_t, which here acts as another state variable. To cope with this problem, we instead define the alternate control variable, $\widehat{\mathcal{C}}_{f,t} = ex_t\mathcal{C}_{f,t}$, or the level of consumption expenditure in the foreign country valued in units of the home country's currency. Define the value function $\widehat{\mathfrak{v}}^f_t(\omega_t)$ as follows:

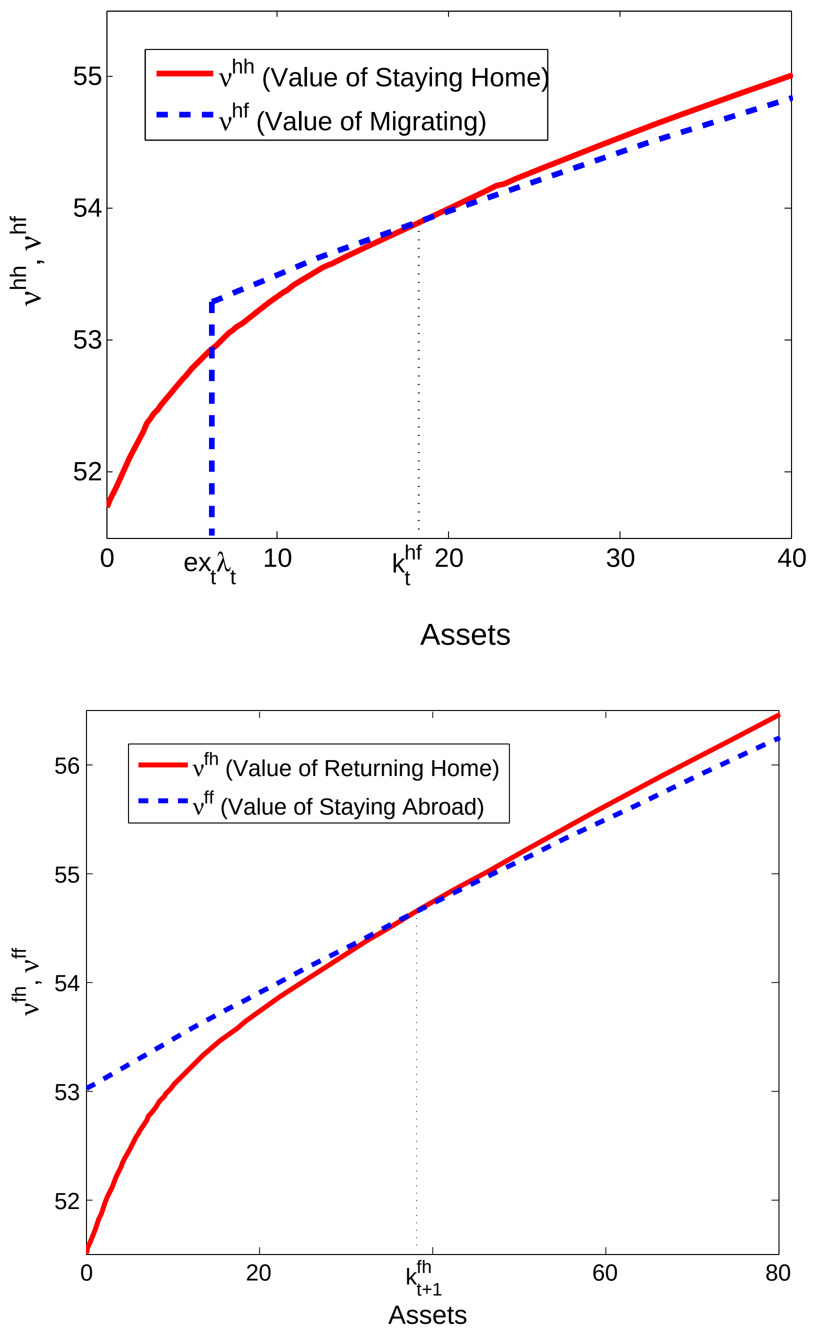
$$\begin{aligned} \widehat{\mathfrak{v}}^f_t(\omega_t) \quad &= \quad E_{\Omega^f_{t+1}}\left[\max_{\widehat{\mathcal{C}}_{f,t}} \log\left(\frac{\widehat{\mathcal{C}}_{f,t}}{ppp}\right) + \beta V^f_{t+1}(k_{t+1}|\Omega^h_{t+1})\right] \\ &\quad\quad s.t.\ k_{t+1} = R[\omega_t - \widehat{\mathcal{C}}_{f,t}] \\ &\quad\quad\quad \widehat{\mathcal{C}}_{f,t} \leq \omega_t \end{aligned} \tag{A-7}$$

It follows that $\mathfrak{v}^f_t(\omega_t) = \widehat{\mathfrak{v}}^f_t(\omega_t) - log(ex_t)$ since $log(\frac{\widehat{\mathcal{C}}_{f,t}}{ppp}) = log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + log(ex_t)$.

I approximate $\widehat{\mathfrak{v}}^f_t(\omega_t)$ and the associated consumption function, $\widehat{\mathcal{C}}^*_{f,t}(\omega_t)$, using the same techniques outlined above for the approximation of $\widehat{\mathfrak{v}}^h_t(\omega_t)$ and $\mathcal{C}^*_{h,t}(\omega_t)$. Once we have approximations of the value functions $\nu^{hh}_t(k_t|\Omega^h_t)$, $\nu^{hf}_t(k_t|\Omega^h_t)$, $\nu^{fh}_t(k_t|\Omega^f_t)$ and $\nu^{ff}_t(k_t|\Omega^f_t)$ for a given period, we can use these to approximate $E_{\Omega^h_t}\left[\beta V^h_{t+1}(k_t|\Omega^h_t)\right]$ $E_{\Omega^f_t}\left[\beta V^f_{t+1}(k_t|\Omega^h_t)\right]$ using linear interpolation methods.

A.3 Examples of Approximated Value Functions

Figure A-1: Value Functions for the Migration and Return Decisions



The top panel depicts the situation in period t=1 when $w_t^h = 7.52$, $\lambda_t = 1.65$, $ex_t = 2.72$. *The bottom panel depicts the situation in period t=2 when* $w_t^f = 15.19$, $\eta_t = -0.84$, $ex_t = 2.72$. *For both panels, T=50,* $\mu_\eta = -0.7$, $\sigma_\eta = 1$, $\mu_h = 2$, $\sigma_h = 0.6$, $\mu_f = 2.5$, $\sigma_f = 0.5$, $\mu_e = 1$, $\sigma_e = 0.05$, $\mu_\lambda = 0.5$, $\sigma_\lambda = 0.1$, $\beta = 0.96$, $ppp = 1$, $R = 1.01$.

Figure A-1 displays graphs of the approximated value functions for an individual who lives for $T = 50$ periods and faces an environment characterized by some reasonable parameters.[20] Assuming that the individual begins period $t = 1$ in the home country, the top panel of Figure A-1 displays approximated value functions relevant for making the migration decision assuming some specified draws of the appropriate random variables. In making a location decision, this worker compares $\nu^{hh}(k_t|\Omega_t^h)$ to $\nu^{hf}(k_t|\Omega_t^h)$, bearing in mind that migration is impossible when $k_t < ex_t\lambda_t$. Notice that $\nu^{hh}(k_t|\Omega_t^h)$ cuts $\nu^{hf}(k_t|\Omega_t^h)$ from below. Figure A-1 highlights the pattern of intermediate selection generated by the model. While sufficiently poor individuals cannot afford migration, individuals with asset stocks that exceed the threshold level k_t^{hf} choose not to migrate because the marginal costs of a migration now exceed the marginal benefits.

Suppose the worker begins period t with an asset stock satisfying $ex_t\lambda_t \leq k_t < k_t^{hf}$ and thus locates in the foreign country during period $t+1$. How long should this worker remain in the foreign country? The bottom panel of Figure A-1 displays the value functions determining whether or not the worker returns to the home country in period $t + 1$, assuming some specified values of the appropriate random variables. The worker possesses an asset stock of $k_{t+1} = R[k_t + ex_t(w_t^f - C_{f,t} - \lambda_t)]$ at the beginning of period $t + 1$, and makes the location decision in this period by comparing $\nu_{t+1}^{hf}(k_t|\Omega_{t+1}^f)$, to $\nu_{t+1}^{ff}(k_{t+1}|\Omega_{t+1}^f)$. The intersection of the value functions determines a threshold asset level, k_{t+1}^{fh}, which depends on Ω_{t+1}^f. If $k_{t+1} < k_{t+1}^{fh}$, the worker remains in the foreign country for another period, but if $k_{t+1} \geq k_{31}^{fh}$, the worker returns home. This model thus predicts that migrants behave as "target savers" who stay in the foreign country until they have accumulated some threshold level of assets. However, the target asset level that will trigger a return migration in a given period, k_{t+1}^{fh}, depends on the model parameters, Ω_{t+1}^f, and the time period $t + 1$.

[20] See the notes under Figure A-1 for the full list of parameters assumed.

A.4 Construction of Census-Based Sampling Weights

One criticism of the MMP is that the data are not representative of Mexico. Only a small number of communities are surveyed each year, and in the earliest waves of the survey, communities in the high migration states of West-Central Mexico were over-represented. There are also some concerns about the sample of households surveyed in the United States. A U.S. sample was not collected for several communities, complicating the interpretation of statistics derived from this data. In fact, this means that migrants may be under-represented in the sample if we only have U.S. surveys for some communities. While the MMP does include sampling weights (equal to the inverse sampling probability), applying these sampling weights produces a sample that is representative of the union of MMP communities, not Mexico as a whole. Such considerations motivate the construction and use of an alternate set of sampling weights. Here I discuss the construction of the weights provided by the MMP, and describe how I use the 1970 Mexican Census, together with some information from the MMP sampling weights, to create an alternate set of weights that address some of these concerns.

We distinguish between two subsamples in the MMP for each community: the Mexican sample, and the U.S. sample. The Mexican sample for a given MMP community j consists of a simple random sample of the households in community j. The MMP weight for a household surveyed in Mexico is the inverse of the sampling probability:

$$\mathcal{W}_j^{MMP,Mex} = \frac{NMex_j}{N_j^{MMP,Mex}}$$

Where $NMex_j$ is the actual number of households in community j, and $N_j^{MMP,Mex}$ is the number of households surveyed in Mexico in community j by the MMP. Similarly, the MMP weight for a household from community j surveyed in the United States is again given by the inverse of the sampling probability:

$$\mathcal{W}_j^{MMP,US} = \frac{NUS_j}{N_j^{MMP,US}}$$

Here NUS_j is the number of community j households that present in the United States, and $N_j^{MMP,Mex}$ is the number of community j households surveyed by the MMP in the United States. In practice, the MMP does not know the actual value of NUS_j, so this is estimated using information about the locations of the children of older households heads in Mexico. Notice that the ratio of the number of community j households based in the United States to the number based in Mexico is given by:

$$USRatio_j^{MMP} = \frac{\mathcal{W}_j^{MMP,US}}{\mathcal{W}_j^{MMP,Mex}} \frac{N_j^{MMP,US}}{N_j^{MMP,Mex}}$$

Thus, for each community j, the MMP-provided weights can be manipulated to reveal the MMP's estimate of the number of US-based households per Mexico-based household for community j. In constructing the Census-based weights, I make use this ratio, but otherwise discard the MMP weights in the construction of the new weights.

The weighting scheme developed and implemented here relies on the fact that most of the sample used to estimate the structural model were young men in 1987, which is the start of the time period of the model. Many of these young men were infants during the 1970 Mexican census. The idea of the weighting scheme pursued here is to adjust the weighting of the sample to match the distribution of young male children across Mexican regions (defined as collections of states) and location sizes in 1970. To do this, I define five Regions: Border States, West Central States, Southern States, South Eastern States, and the Distrito Federal (which contains Mexico City).[21] We also define four Location Sizes based on 1970 population: $0-2499$, $2500-14999$,$15000-100000$,> 100000. Let r index a region and let ℓ index a location size category. Based on the expansion factors in the 1970 Census, I estimate the number of young males aged 0-10 in the 1970 Census for each r,ℓ cell: $N_{r,\ell}^{1970}$. Each community j can be assigned to an r,ℓ cell using the state of the community and the 1970 population of the community (which is included in the COMMUN file). Let $N_{r,\ell}^{S,Mex}$ refer to the number of individuals originating from r,ℓ communities in the structural model sample surveyed in Mexico. Also, let $N_{r,\ell}^{S,US}$ refer to the number of individuals originating from r,ℓ communities in the sample that are surveyed in Mexico.

If no Mexican households resided in the United States, then one could generate a Census-based weight for an individuals in an r,ℓ cell in the sample by simply taking the ratio $N_{r,\ell}^{1970}/N_{r,\ell}^{S,Mex}$. Accounting for the U.S. sample requires only a minor adjustment of this basic idea. Let $USRatio_{r,\ell}$ represent the number of U.S. households per Mexican household observed in cell r,ℓ. Let $\mathcal{W}_{r,\ell}^{Cen,Mex}$ and $\mathcal{W}_{r,\ell}^{Cen,US}$ refer to the Census-based weights for an individual from cell r,ℓ surveyed in Mexican and U.S., respectively. These wights should

[21]The Border States category includes Baja California Norte, Baja California Sur, Coahuila, Chihuahua, Nuevo Leon, Sonora, and Tamaulipas. The West Central region includes the states Aguascalientes, Colima, Durango, Guanajauto, Jalisco, Michoacan, Nayarit,Queretaro, San Luis Potosi, Sinaloa, and Zacatecas. The Southern region includes the states Guerrero, Hidalgo, Mexico, Morelos, Oaxaca, Puebla, Tlaxcala, and Veracruz. The Souther Eastern region includes the states Campeche, Chiapas, Quintana Roo, Tabasco, and Yucatan.

satisfy the following two conditions:

$$\begin{aligned} \mathcal{W}_{r,\ell}^{Cen,Mex} N_{r,\ell}^{S,Mex} + \mathcal{W}_{r,\ell}^{Cen,US} N_{r,\ell}^{S,US} &= N_{r,\ell}^{1970} \\ \mathcal{W}_{r,\ell}^{Cen,US} N_{r,\ell}^{S,US} &= \mathcal{W}_{r,\ell}^{Cen,Mex} N_{r,\ell}^{S,Mex} USRatio_{r,\ell} \end{aligned}$$

Where $USRatio_{r,\ell}$ is an estimate of the number of the ratio of cell r, ℓ households that reside in United States relative to the number that reside in Mexico. I estimate this ratio by taking the average of the $USRatio_j^{MMP}$ measure across the MMP communities that fall into cell r, ℓ.[22] The weights can thus be calculated as:

$$\begin{aligned} \mathcal{W}_{r,\ell}^{Cen,Mex} &= \frac{N_{r,\ell}^{1970}}{N_{r,\ell}^{S,Mex} + N_{r,\ell}^{S,Mex} USRatio_{r,\ell}} \\ \mathcal{W}_{r,\ell}^{Cen,US} &= \mathcal{W}_{r,\ell}^{Cen,Mex} USRatio_{r,\ell} \frac{N_{r,\ell}^{S,Mex}}{N_{r,\ell}^{S,US}} \end{aligned}$$

Relative to the MMP weights, this weighting scheme reduces the relative weight given to an observation from an r, ℓ cell that has been oversampled by the MMP relative to the relevant population share of this cell. Thus, the weighting scheme addresses the over-representation of high migration states. Additionally, the weighting scheme addresses a problem created by missing U.S. samples in some communities. In an r, ℓ cell where some of the MMP communities are missing a U.S. sample, then the U.S. observations that are available for this cell should be given more weight. The construction of the the $\mathcal{W}_{r,\ell}^{Cen,US}$ weight corrects for this, as long as the $USRatio_{r,\ell}$ measure is reasonably accurate.

It should be noted the MMP sample that I use does not contain individuals from the Distrito Federal (Mexico City), or from the Southeast states on the Yucatan Peninsula. Since these are relatively low migration regions, my results may still suffer from some selection bias, even with this weighting scheme. Specifically, migrants might be over-represented in my sample, and estimates of the cost of migration could be understated.

[22] For some cells, $USRatio_{r,\ell}$ cannot be calculated in this manner because there is no U.S. sample for an MMP community that falls into these cells. In such cases, we calculate $USRatio_{r,\ell}$ as the average of $USRatio_j^{MMP}$ for MMP communities belonging to Region r.

A.5 Identification

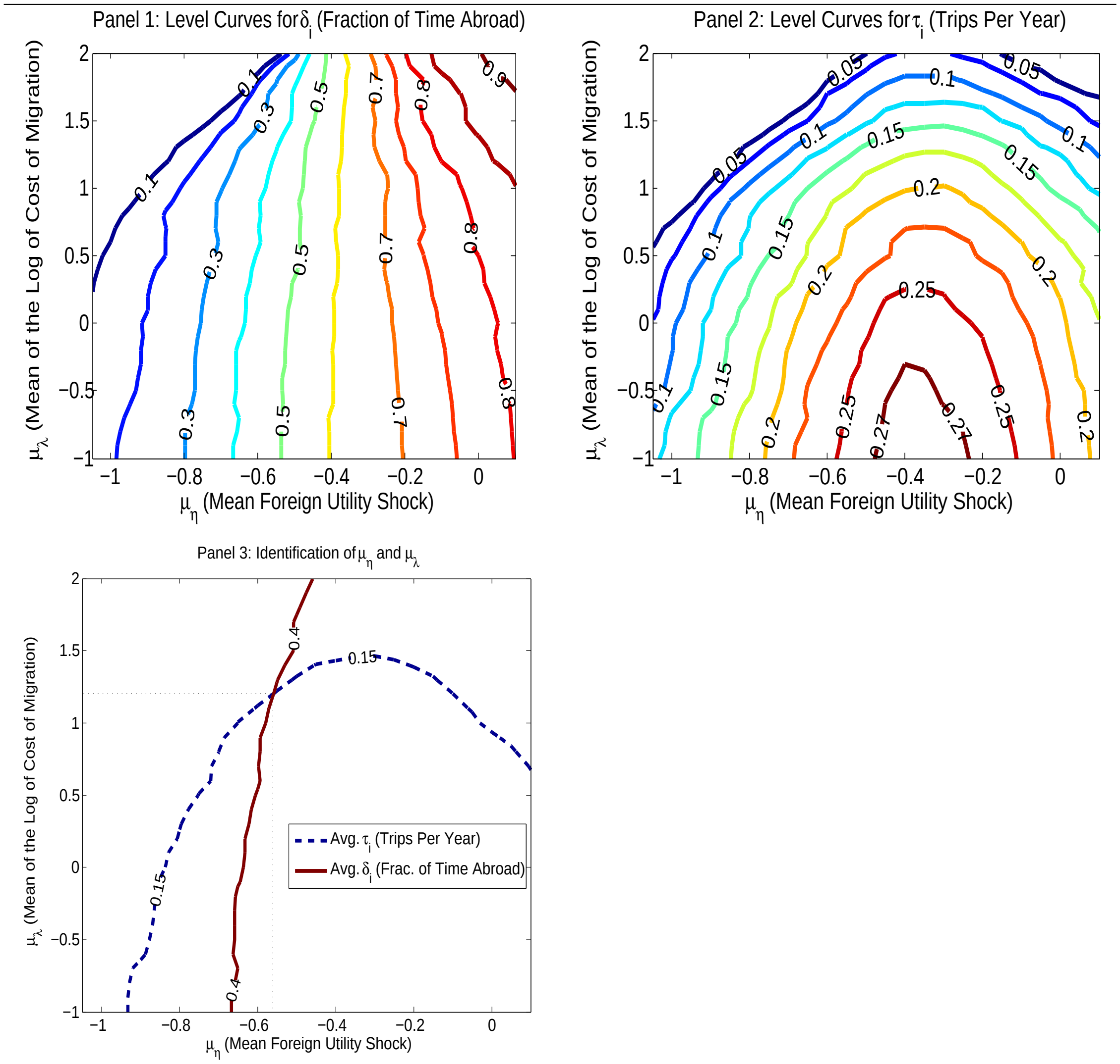
Ideally, we would like to have data with a complete record of location decisions, asset levels, and wage outcomes for each individual in every time period. With such data, we could express the probability of outmigration to the U.S. conditional on the observables, $Prob(L_t = 1|L_{t-1} = 0, k_t, w_t, ex_t)$, as a simple function of the unobserved cost of migration. Furthermore, we could express the probability of return migration to Mexico conditional on the observables, $Prob(L_t = 0|L_{t-1} = 1, k_t, w_t, ex_t)$, as a simple function of the unobserved preference shock η_t. One could then successfully identify the parameters of the structural model.

Although we do not have complete data wage realizations or asset stock levels for individuals in the sample, we can still identify the structural parameters. As explained in the text, the income data that are available from the MMP and the ENIGH permit the estimation of income distributions in both Mexico and the United States. Given these distributions, and an initial distribution of assets identified from the MFLS data, one can employ simulation techniques to approximate the expected values of the migration pattern variables and their squares, $\{m_i^j\}_{j\in\{2,4,6,8\}}$, δ_i, δ_i^2, τ_i, and τ_i^2. The main parameters of the structural model, μ_η, σ_η,μ_λ, can be identified through their unique effects on the expectations of these migration pattern variables given the wage distribution.

Consider the parameters μ_η and μ_λ, and their relation to the observables τ_i and δ_i.[23] As μ_λ increases, we expect τ_i to decline since λ_t acts as the price of a single migratory trip. However, as μ_η increases, we expect τ_i to first increase and then decrease, as explained in Section 3. Panel 1 of Figure A-2 displays level curves for the average value of τ_i when the model is simulated 1000 times for different combinations of μ_η and μ_λ. The simulations involve different randomly drawn sequences of home and foreign wages, and these sequences are held fixed as the parameter combinations change. Now consider δ_i, which we expect to decrease as μ_λ increases and individuals take fewer migratory trips. We also expect δ_i to increase as μ_η increases and foreign residence becomes more attractive. Panel 2 of Figure A-2 displays level curves for the average value of δ_i when the model is simulated 1000 times for different combinations of μ_η and μ_λ. Panel 3 of Figure A-2 demonstrates how a given combination of expected values for τ_i and δ_i can identify the parameters μ_η and μ_λ through the intersection of the level curves associated with the combination. The dispersion parameter σ_η is then related to the variances of both δ_i and τ_i. The expected values for δ_i^2, and τ_i^2 may therefore identify σ_η and σ_λ.

[23] Recall that τ_i represents the number of observed trips divided by the number of years an individual is in the sample, and that δ_i represents the fraction of an individual's observed life spent in the United States.

Figure A-2: Identification of μ_η and μ_λ



For all panels,$\sigma_\eta = 0.5$, $\mu_h = 2$, $\sigma_h = 0.25$, $\mu_f = 2.5$, $\sigma_f = 0.25$, $\mu_e = 0.5$, $\sigma_e = 0.05$, $\sigma_\lambda = 0.1$ $\beta = 0.96$, $ppp = 1$ $R = 1.01$. For each point used to make these graphs, the mean levels of δ_i (the fraction of time spent in the foreign country) and τ_i (the number of trips divided by the number of number of periods observed) were recorded for 1,000 simulated life histories for an individual with $T = 50$ observed for T periods.

A.6 Moments used in Estimation

Here I provide a more specific enumeration of the 93 moments used to estimate the model:

- The basic set of eight migration measures, m_i^{17}, m_i^{19}, m_i^{21}, m_i^{23}, m_i^{25}, δ, δ^2, and τ are interacted with eight dummy variables for each of the following characteristics: 1) Constant, 2) Reach Adulthood between 1989 and 1992, 3) Reach Adulthood 1993 or after, 4) Urban Area in Mexico, 5) Father was a Migrant, 6) Education 4-6 Years, 7) Education 7-9 Years, 8) Education over 9 Years. This set accounts for 64 moments.

- The basic set of eight migration measures above, but without m_i^{25}. These are interacted with dummy variables indicating the following: 1) Reach Adulthood 1993 or after, and Non-Urban area in Mexico, 2) Reach Adulthood 1993 or after, and Eduction between 4-9 years. I don't consider m_i^{25} conditional on these characteristics because of small sample sizes. This set accounts for 14 moments.

- The five Trip Duration variables listed in the $\mathfrak{p}_{2i}$ vector, interacted with dummy variables indicating the following: 1) Constant, 2) Reach Adulthood after 1989, 3) Education between 4-9 years. This set accounts for 15 moments.

A.7 Calculating the Asymptotic Variance of the Parameter Estimates

We use the expansion method outlined in Newey and McFadden (1994), as applied to a two-stage Method of Simulated Moments estimator by Gourinchas and Parker (2002), to calculate the standard errors of the parameter estimates in the model. Define $G_{\Pi^M} = E\left[\frac{\partial g(\mathfrak{p}_i,\Pi)}{\partial \Pi^M}\right]$, which is a $N^g \times N^M$ matrix of expected partial derivatives, where N^g is the number of moment conditions and N^M is the number of parameters in Π^M. Recall that $\Pi = [\Pi^M \;\; \Pi^{w,US} \;\; \Pi^{w,Mex} \;\; \Pi^A]$ refers to the vector of combined first stage parameters. The vectors $\Pi^{w,US}$, $\Pi^{w,Mex}$ and Π^A have lengths N^{US}, N^{MEX}, and N^A respectively. Then we can define $G_{US} = E\left[\frac{\partial g(\mathfrak{p}_i,\Pi)}{\partial \Pi^{w,US}}\right]$, a $N^g \times N^{US}$ matrix of expected partial derivatives, as well as $G_{MEX} = E\left[\frac{\partial g(\mathfrak{p}_i,\Pi)}{\partial \Pi^{w,Mex}}\right]$, a $N^g \times N^{US}$ matrix of expected partial derivatives, and $G_A = E\left[\frac{\partial g(\mathfrak{p}_i,\Pi)}{\partial \Pi^A}\right]$, a $N^g \times N^A$ matrix of expected partial derivatives. Let V_{US}, V_{MEX}, and V_A represent the asymptotic covariance matrices for the first stage parameter estimates. Since the three sets of first stage parameters are all estimated using different data sets, we assume that the parameter estimates for $\Pi^{w,US}$, $\Pi^{w,Mex}$ and Π^A are uncorrelated.

Let Π_o^M refer to the true value of the Π^M parameters, and let I refer to the number of individual observations on the moments conditions, $g(\mathfrak{p}_i, \Pi)$. We assume that these observed moment conditions are uncorrelated with the observed moment conditions used to estimate Π^{US}, Π^{Mex}, and Π^{A} in the first-stage, an assumption that may be defended on the grounds that the estimation of these parameters (even Π^{US}) relies on data that are mostly different from those used to construct the migration moments. Then using the Slutsky and central limit theorems, one may show that the term $\sqrt{I}(\Pi^{M*} - \Pi^{M}_{o})$ converges in distribution to a normal random variable with the following asymptotic covariance distribution:

$$
\begin{aligned}
V_{\Pi^M} &= (G'_{\Pi^M} W G_{\Pi^M})^{-1} G'_{\Pi^M} W \, [\alpha \Omega_g + \psi_{US} G'_{US} V_{US} G_{US} \\
&\qquad + \psi_{MEX} G'_{MEX} V_{MEX} G_{MEX} \\
&\qquad + \psi_A G'_A V_A G_A] \, W G_{\Pi^M} (G'_{\Pi^M} W G_{\Pi^M})^{-1} \qquad \text{(A-8)}
\end{aligned}
$$

Where $\Omega_g = E[g(\mathfrak{p}_i, \Pi_o) g(\mathfrak{p}_i, \Pi_o)']$, $\alpha = \lim_{I\to\infty}(1 + \frac{I}{\rho})$, $\psi_{US} = \lim_{I\to\infty} \frac{I}{J_{US}}$, $\psi_{MEX} = \lim_{I\to\infty} \frac{I}{J_{MEX}}$, and $\psi_A = \lim_{I\to\infty} \frac{I}{J_A}$. Here J_{US}, J_{MEX}, and J_A refer to the numbers of observations used to estimate the various first-stage parameters. Although Equation A-8 contains a number of terms involving limits and expectations of random variables, we estimate V_{Π^M} by replacing any such terms with their empirical counterparts.

A.8 Predicting Border Enforcement

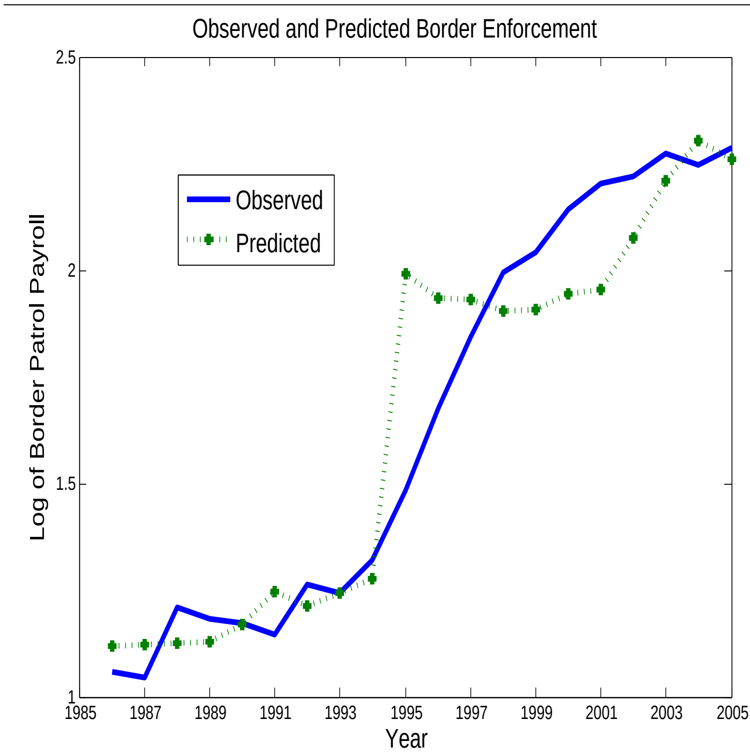
One robustness check performed in the paper is to replace the observed border enforcement series with one that has been predicted using an instrumental variable. Following Hanson and Spilimbergo (1999), I use real defense spending as an instrument for the intensity of border enforcement. As they point out, border enforcement might be negatively correlated with defense spending if these two trade-off in budgetary allocations. However, these might also be positively correlated if border policing is cast politically as a national security issue (as was the case in the wake of September 11th). I use an annual historical defense spending series from the White House's Office of Management and Budget to create a log real defense spending variable (log of millions of dollars). The first stage results are shown in Table A.8. Before 1995, defense spending is negatively correlated with border enforcement, but this reverses after 1995. Figure A.8 plots the observed and predicted series for the log of the Border Patrol payroll. Compared to the observed series, the predicted series exhibits less fluctuation before 1995, rises more quickly after the Peso Crisis, and does not rise in the late 1990s. The lower degree of fluctuation suggests that the predicted series is less likely to be picking up endogenous responses in border enforcement to transitory shocks to the incentives to migrate. It is possible that the continued rise of border enforcement at the end of the 1990s was a response to the tight labor market conditions in the United States. The predicted series does not exhibit an expansion during this period, and so structural estimates using this predicted series should not be biased by a policy response to the boom of the late 1990s.

Table A-1: Predicting Border Enforcement

Constant	8.75
	(7.65)
Crash	-20.04**
	(9.17)
log Def. Spending	-0.589
	(0.59)
Crash X log Def. Spending	1.63**
	(0.72)
N	20

*Note: Stars Signify the following: *** significant at the 0.01 level, ** significant at the .05 level, * significant at the 0.1 level. Standard Errors are reported in parentheses.*

Figure A-3: Comparison of Observed and Predicted Border Enforcement



A.9 Estimating the Aggregate State Process

To estimate a discrete-state Markov process for income in the United States, I work with the real GDP series for the United States from 1980-2005 from the IMF's *International Financial Statistics*, and apply the method of Tauchen (1986). Let $\widetilde{y}_t$ denote the log of real GDP in year t, where this variable has been detrended (assuming a linear trend). The variable of interest is lagged growth in detrended GDP, $y_t = \widetilde{y}_{t-1} - \widetilde{y}_{t-2}$. We assume that y_t follows a very simple auto-regressive process:

$$y_t = \alpha y_t + u_t \tag{A-9}$$

Where $u_t \sim N(0, \sigma_u)$. Tauchen's method provides a way to discretize this process into a three-state discrete process. Specifically, assume that there are three mass points, $\overline{y}^1$, $\overline{y}^2$, and $\overline{y}^3$. I choose these to be -1.25σ, 0, and 1.25σ, respectively. Let $w = \frac{\overline{y}^2 - \overline{y}^1}{2}$. Then we can divide the real line into three regions that correspond to States 1, 2, and 3, respectively: $(-\infty, \overline{y}^1 + w)$, $[\overline{y}^1 + w, \overline{y}^2 + w]$, and $(\overline{y}^2 + w, \infty)$, respectively. For a given year, t, we can assign a state S_t to the year t by determining in which region y_t falls. For example, the economy is in State 1 if $y_t < \overline{y}^1 + w$.

To get the transition probabilities of the form π_{jk}, we revert back to the continuous autoregressive process and we suppose that $y_{t-1} = \overline{y}^j$. Then π_{jk}, the probability of transitioning from State j from State k, is simply the probability that the continuous process y_t moves into the region associated with State k if $y_{t-1} = \overline{y}^j$. For example, for π_{12}, we have:

$$\pi_{12} = \Phi\left(\frac{\overline{y}^2 - \alpha\overline{y}^1 + w}{\sigma_u}\right) - \Phi\left(\frac{\overline{y}^2 - \alpha\overline{y}^1 - w}{\sigma_u}\right) \tag{A-10}$$

Based on this procedure, years 1990-1991 belong to the Low State ($S_t = 1$), years 1997-1999 belong to the High State, ($S_t = 3$), and all other years in the sample belong to the Medium State, ($S_t = 2$). The transition matrix, with elements π_{jk} is estimated to be:

$$\pi = \begin{pmatrix} 0.35 & 0.26 & 0.19 \\ 0.46 & 0.48 & 0.46 \\ 0.19 & 0.26 & 0.35 \end{pmatrix} \tag{A-11}$$

Table A-2 displays the parameter estimates for the U.S. income equation when the aggregate state is allowed to affect income. Income is substantially higher, relative to State 1 when the economy is in State 2 or 3.

Table A-2: US Income and Aggregate Shocks

	$log(w^{US})$
Constant	2.85***
	(0.13)
Age	-0.01***
	(0.00)
Education: 4-6 Years	0.11*
	(0.07)
Education: 7-9 Years	0.15**
	(0.08)
Education: 10-12 Years	0.16**
	(0.09)
Education: More than 12 Years	0.18*
	(0.10)
Time Trend	-0.01
	(0.01)
State 2	0.18*
	(0.06)
State 3	0.22**
	(0.08)
σ	0.53***
	(0.00)
N	1,350

*Note: Stars Signify the following: *** significant at the 0.01 level, ** significant at the .05 level, * significant at the 0.1 level. Standard Errors are reported in parentheses. All estimates have been derived using a Method of Moments estimator. Labor income is measured in thousands of units of real pesos or dollars. The dependent variable is the log of twelve times an observed monthly income, since estimation of the structural model proceeds taking a year as the length of a period. Nominal wages are deflated using the Mexican and U.S. CPI series from the June 2010 release of the IMF's International Financial Statistics with 2000 as the base year.*