Repeated Circular Migration: Theory and Evidence

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Abstract

This paper contributes to the literature on temporary migration by developing and solving 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. Counterfactual policy experiments suggest that raising the growth of border enforcement reduces the total amount of time that individuals spend in the United States, even if the durations of individual trips to the U.S. increase. The cost of migration and an individual's preference for residence in Mexico are allowed to vary with education, but I do not find any statistically significant differences in these parameters. The model and parameter estimates may be useful in analyzing the incentives for workers to participate in some recently proposed guestworker programs.

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Keywords: Circular Migration, Undocumented Migration, Mexico-U.S. Migration

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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. Examining data collected over the period 1987-1992, Massey and Espinosa (1997) report that the Mexican migrants in their sample, most of which engaged in undocumented migration, made an average of over 3 trips to the U.S. before the time of the survey.

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 analyzed how the duration and frequency of migratory trips vary with individual characteristics such as education and variables such as the intensity of border enforcement. However, since this literature typically uses reduced-form methods, it reaches few conclusions about the underlying incentives and behav-

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

ioral parameters that govern migration. Yet, it is precisely these structural parameters that one needs in order to understand how migration behavior will change as important economic or policy variables change.

Data from the Mexican Migrant Project (MMP) reveal heterogeneity in the pattern of migration across individuals with different levels of education. Those with intermediate levels of education are found to take more trips and spend a larger fraction of their observed lives in the United States. Reduced-form methods are unable to shed light on the source of this heterogeneity, since underlying factors that may be responsible, such as differences in location preferences or the full cost of migration, are either unobservable or not fully captured by available data. This provides a further justification for the estimation of a structural model that may explain these features of the data.

This paper develops a dynamic model of circular migration that explains the behavior of migrants as a function of the international wage gap, a preference for residence in the home country, and the cost of migration. The model advances the literature by considering an environment in which individuals are allowed to hold assets and make multiple trips to a foreign country. Estimable models of circular migration allowing for multiple trips and savings are nearly absent from the literature, despite the prominence of these two features in the pattern of undocumented Mexican migration.[2] The principal theoretical results of the model developed here include the following: (1) The model predicts a pattern of behavior in which workers migrate to a foreign country, accumulate a stock of assets, and return home to consume out of this stock before initiating another migratory trip. (2) The model predicts that migrants are selected from the intermediate regions of the wealth distribution, a result consistent with recent empirical work. (3) Policies that raise the cost of migration may reduce the total amount of time that migrants spend in a foreign country while increasing the length of each observed migratory trip.

Using data on migrants and non-migrants from the MMP, I estimate the parameters of the

[2]As Massey et al. (2003), Mexican migrants often the follow the pattern of migrating to the U.S., accumulating some stock of savings, and then returning to Mexico to purchase assets or consumptions goods at home before initiating another migratory trip.

structural model through the Method of Simulated Moments. The empirical results suggest the following: (1) Increases in the intensity of U.S. border enforcement lead to significant increases in the cost of migration, causing migrants to take fewer but longer migratory trips. (2) Individuals exhibit a preference for residence in Mexico, and this preference appears to be strongest for individuals with higher levels of education, although imprecise estimation prevents one from drawing firm conclusions. (3) The structural parameter estimates do not reveal a significant relationship between education and the cost of migration. Overall, the results suggest that differences in wages, rather than in migration costs or preferences, account for the variation in migration behavior observed across individuals with different levels of education.

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

2.1 Empirical Work on Mexican Migration

The existing empirical work on temporary Mexican migration focuses on explaining the duration of temporary trips in the United States. This literature suggests that trip durations vary across educational groups, although there does not appear to be a consensus about the nature of this relationship. While Massey and Espinosa (1997) and Reyes and Mameesh (2002) find that higher levels of education are associated with a lower hazard rate of returning to Mexico, Lindstrom (1996) presents evidence of a positive effect. The size and economic characteristics of one's community of origin also matter. Lindstrom (1996) finds that migrants from larger communities tend to have higher hazard rates, a pattern observed by Reyes (2004) among the undocumented migrants in her sample. Reyes (2004) concludes that migrants from heavily agricultural areas also tend to have higher hazard rates. Accumulated wealth appears to exert an additional influence on the pattern of migration. Both Massey and Espinosa (1997) and Reyes (2004) find that the possession of certain assets, including land and residential property, is associated with a higher hazard rate of returning.

The empirical literature on circular Mexican migration indicates that individuals with different characteristics tend to engage 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 the seminal work of Borjas (1987) on the selectivity of migration in a static Roy model, a string of empirical studies have argued that Mexican migrants tend to be negatively selected on the basis of human capital or skills, and that successive waves of Mexican migrants have become more negatively selected. [3] For example, Borjas and Katz (2007) conclude that Mexican immigrants tend to have significantly lower levels of education relative to U.S. natives and non-Mexican immigrants.[4] However, alternate conclusions emerge from a number of recent papers disputing the negative selection of Mexican immigrants. Using Mexican census data, Chiquiar and Hanson (2005) generate counterfactual Mexican wage densities for migrants in the U.S. and conclude that migrants would belong in the middle of the Mexican wage distribution if they were observed working in Mexico. This finding is also supported by Lacuesta (2006) and Orrenius and Zavodny (2005), who specifically analyze undocumented migrants. A pattern of intermediate selection can be explained by a theoretical model in which 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

[3] It is typically impossible to differentiate between undocumented and legal migrants in U.S. and Mexican census data, and so conclusions about the selectivity of undocumented immigrants are often drawn from empirical work considering the entire population of Mexican migrants. See Hanson (2006) on this point.

[4] One can also find empirical support for the claim that Mexican migrants are drawn from the lower tail of the Mexican wage distributions. Using Mexican data, both Ibarraran and Lubotsky (2007) and Moraga (2006) find that Mexican migrants tend to have lower levels of education than non-migrants in Mexico, while Moraga (2006) also finds that non-migrants in Mexico experience higher wages

be prohibited from migrating if they are unable to borrow to pay for the costs of migrating.

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.

2.2 Theoretical Models of Circular Migration

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, which Djajic and Milbourne incorporate by assuming higher marginal utility to consumption in the home country. The pattern that emerges is that individuals migrate, build up a stock of savings, and return home to consume out of savings at home. Berninghaus and Seifert-Vogt (1993) provide a more 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. [5]

A number of papers examine models with different motivations for return migration, most

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

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. (Dustmann and Kirchkamp 2002, Mesnard 2004) Price differences between the home country and the foreign country could also motivate this pattern. If the foreign country offers higher wages, but the price of consumption is lower in the home country, migrants again have an incentive to accumulate savings abroad and return home to consume. 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 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. The analysis of undocumented Mexican migration therefore demands the use of a more flexible model capable of generating and explaining repeated circular migration.

Although Colussi (2006) develops and estimates a structural model allowing for repeated circular migration using data on undocumented Mexican immigrants, his model assumes that migrants do not accumulate assets. This simplifies the model, allowing for the tractable analysis of network effects. However, by ignoring asset accumulation, this approach assumes away an apparently crucial aspect of migrant behavior. Angelucci (2005) does consider a two-period model of repeated repeated circular migration with savings in the context of undocumented Mexican migration, but does not expand the scope of the model or attempt to estimate the model's parameters. Rendon and Cuecuecha (2007) use Mexican data to estimate a model permitting both repeated circular migration and savings, but they do not consider the effect of border enforcement or allow the model parameters to vary with individual characteristics.

3 A Model of Repeated Circular Migration

3.1 The Basic Environment

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 wage at time t in the home country, w_t^h, and his or her real wage 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: $log(ex_t){\sim}N(\mu_e, \sigma_e^2)$.

3.2 Period Utility

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 flow of utility, η_t. During each period of residence in the foreign country, a given individual receives a different draw from the distribution of this preference shock: $\eta_t \sim N(\mu_\eta, \sigma_\eta^2)$. 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:

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

3.3 The Cost of Migration

Every time the migrant enters the foreign country, he or she must pay a monetary migration cost, λ_t, which is 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. This assumption seems justified for two reasons. First, as indicated by 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.

3.4 Capital Markets and Asset Accumulation

Following Mckenzie and Rapoport (2007), individuals are unable to borrow in this model. Although this assumption is extreme, it may reasonably capture the credit market imperfections most likely 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 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 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.

3.5 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.[6] After making a location decision, the worker receives information about the remaining stochastic variables and then makes a consumption decision.

[6]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.

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

$$\begin{aligned}
\nu_t^{hh}(k_t|\Omega_t^h) &= \max_{\mathcal{C}_{h,t}} \log(\mathcal{C}_{h,t}) + \beta E_{\Omega_{t+1}^h}\left[V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right] \qquad (4)\\
&\quad s.t.\ k_{t+1} = R[k_t + w_t^h - \mathcal{C}_{h,t}]\\
&\quad \mathcal{C}_{h,t} \le k_t + w_t^h\\
\nu_t^{hf}(k_t|\Omega_t^h) &= E_{\eta_t, w_t^f}\left[\max_{\mathcal{C}_{f,t}} \log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + \eta_t + \beta E_{\Omega_{t+1}^f}\left[V_{t+1}^f(k_{t+1}|\Omega_{t+1}^f)\right]\right] \qquad (5)\\
&\quad s.t.\ k_{t+1} = R\left[k_t + ex_t(w_t^f - \mathcal{C}_{f,t} - \lambda_t)\right]\\
&\quad \mathcal{C}_{f,t} \le \frac{k_t}{ex_t} + w_t^f - \lambda_t
\end{aligned}$$

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:

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

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 $\nu_t^{hf}(k_t|\Omega_t^h)$.

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.

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.

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:

$$\begin{aligned}
\nu_t^{fh}(k_t|\Omega_t^f) &= E_{w_t^h}\left[\max_{\mathcal{C}_{h,t}} \log(\mathcal{C}_{h,t}) + \beta E_{\Omega_{t+1}^h}\left[V_{t+1}^h(k_{t+1}^h|\Omega_{t+1}^h)\right]\right] \qquad (8)\\
&\quad s.t.\ \ k_{t+1} = R[k_t + w_t^h - \mathcal{C}_{h,t}]\\
&\quad \mathcal{C}_{h,t} \leq k_t + w_t^h\\
\nu_t^{ff}(k_t|\Omega_t^f) &= \max_{\mathcal{C}_{f,t}} \log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + \eta_t + \beta E_{\Omega_{t+1}^f}\left[V_{t+1}^f(k_{t+1}^f|\Omega_{t+1}^f)\right] \qquad (9)\\
&\quad s.t.\ \ k_{t+1}^f = R[k_t + ex_t(w_t^f - \mathcal{C}_{f,t})]\\
&\quad \mathcal{C}_{f,t} \leq \frac{k_t}{ex_t} + w_t^f
\end{aligned}$$

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:

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

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

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.

3.6 Numerical Solution

3.6.1 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

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

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 interpolation methods that rely on the method of endogenous gridpoints developed by Carroll (2006). The Appendix describes these methods in greater detail.

To get a feel for the nature of the worker's optimal behavior, let's examine the relevant value functions for a worker with a 100 period horizon who we observe in period 30 and who lives in an environment governed by some reasonable parameters.[7] I have assumed that the worker has observed a home wage of $w^f_{30} = 20$, a real exchange rate of $ex_{30} = 11$, and a migration cost of $\lambda_{30} = 9$. The top panel of Figure 1 displays graphs of the resulting value functions. In making

[7]The parameters used in this example are as follows: $\mu_\eta = -1.5$, $\sigma_\eta = .25$, $\mu_h = 2.75$, $\sigma_h = .75$, $\mu_f = 3$, $\sigma_f = .6$, $\mu_e = 2.4$, $\sigma_e = .15$, $\mu_\lambda = 2$, $\sigma_\lambda = .5$ $\beta = .97$, $ppp = 0.1689$ $R = 1.0109$.

a location decision, this worker compares $\nu_{30}^{hh}(k_{30})$ to $\nu_{30}^{hf}(k_{30})$, bearing in mind that migration is impossible when $k_{30} < ex_{30}\lambda_{30} = 99$. To depict the constraint, we have set $\nu_{30}^{hf}(k_{30}) = 0$ for $k_{30} < 99$. Notice that $\nu_{30}^{hh}(k)$ cuts $\nu_{30}^{hf}(k)$ from below. Figure 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_{30}^{hf} choose not to migrate because the marginal costs of a migration now exceed the marginal benefits.

Suppose the worker begins period 30 with an asset stock satisfying $99 \leq k_{30} < k_{30}^{hf}$ and thus locates in the foreign country during period 31. How long should this worker remain in the foreign country? The bottom panel of Figure 1 displays the value functions determining whether or not the worker returns to the home country in period 31, assuming a realized foreign wage of $w_{31}^{f} = 20$, preference shock $\eta_{31} = -2$, and exchange rate of $ex_{31} = 11$. The worker possesses an asset stock of $k_{31} = R[k_{30} + ex_{30}(w_{30}^{f} - C_{f,30} - \lambda_{30})]$ at the beginning of period 31, and makes the location decision in this period by comparing $\nu_{31}^{hf}(k_{31})$, to $\nu_{31}^{ff}(k_{31})$. The intersection of the value functions determines a threshold asset level, k_{31}^{fh}, which depends on Ω_{31}^{f}. If $k_{31} < k_{31}^{fh}$, the worker remains in the foreign country for another period, but if $k_{31} \geq k_{31}^{fh}$, 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}^{fh}, depends on the model parameters, Ω_{t}^{f}, and the time period t.

3.6.2 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. [8] In a one-trip model, if the cost of migration increases, migrants must spend a longer amount of time in the foreign country, accumulating extra wealth to recoup this cost. Argumentation in this vein has served as the backbone for one popular critique of U.S.

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

border policy. As Massey et al. (2003) contend, since the deterrent effect of border enforcement appears to be small, increases in the cost of migration caused by intensified border enforcement should be expected to increase the length of stay of undocumented migrants in the United States. Therefore, 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 optimal length of stay 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 given 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 2 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 500 simulated individuals observed for the first 50 periods of life. Unless otherwise noted, the parameters are the same as those used to generate the value functions in Figure 1.

Panels 1 and 2 of Figure 2 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, migrants find that they can stay in the foreign country for a longer stretches of time before the marginal disutility of spending time in the foreign country outweighs the marginal benefits. At some point, however, continued increases in μ_η result in a lower average number of trips taken as migrants spend a greater fraction of their life on fewer but longer trips to the foreign country. It is important to note that, even when $\mu_\eta \geq 0$, the fraction of time spent in the foreign country will not necessarily be close to unity. Depending on the parameterization of the model, even if the migrant prefers to reside in the foreign country, it still may optimal to return home to take advantage of the lower price of consumption in the home country.

Panels 3 and 4 of Figure 2 suggests that, as μ_λ rises, the average number of trips taken by a migrant decreases. This result is expected given the role of μ_λ in determining the monetary cost of each trip. Panel 3 suggests that as μ_λ increases, average trip duration increases as migrants must now spend a longer time in the foreign country to recoup the cost of each trip. However, as Panel 4 suggests, the average fraction of one's life spent in the foreign country seems to monotonically decline as μ_λ increases. These simulation results are partly consistent with the argument advanced by Massey et al. (2003) in that the model suggests a positive relationship between the cost of migration and the duration of any particular trip. However, this relationship does not necessarily support the conclusion that increases in the cost of migration increase the total amount of time that an individual spends in the foreign country.

4 Data

Every year since 1987, the Mexican Migration Project (MMP) has conducted household interviews in Mexican communities. The database also includes survey responses from a pilot project conducted in 1982 and 1983. After selecting a particular community for inclusion in the database, the Project randomly selects households within that community for the survey. 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.

Although the MMP does not follow up on the same households year after year, the life histories of the household heads are used to construct panel data tracking the characteristics and migration behavior of these individuals over time. The demographic variables tracked every year include education, presence in a marriage or consensual union, and the number of children currently living or who have ever lived as of that year. The data record whether or not an individual spent any time in the U.S. in a given year, if a new trip to the U.S. was made in that year, what documentation, if any, was used in making such a trip, and how many months the individual spent in the United States. For each year, the data also track an individual's primary state and city of residence in either Mexico or the United States. Additionally, the data record whether or not an individual's parents and siblings have acquired any migration experience before or during a given year.

The MMP data include a limited number of occupational or labor variables in each year of an individual's life. For a given year, the data record the duration of an individual's job, the occupation of his or her primary job, whether or not the individual experienced a job change, and whether the job offers Social Security or pension benefits. Wages are not observed in every period, but the data do provide detailed information on wages and the duration of employment for the first and most recent trips, if any, made to the United States, and the first and most recent internal migrations, if any, in Mexico made by an individuals. Although the data do not directly measure wealth in every period, they do record an individual's holdings of certain asset types (hectares of land, parcels of land, properties, and businesses) in every year.

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 overrepresent 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 for even some permanent migrants to be included in the MMP data.

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 migrants after 1986. I also restrict the analysis to explain adult behavior. 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.

I exclude those individuals older than 25 years of age upon reaching adulthood as defined in this paper.

The main sample of this study consists of 1165 observations of the life histories of male household heads who reached adulthood during or after 1987. The sample therefore 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[9]. I have restricted the sample to those individuals with less than 17 years of education. This is done because highly educated individuals may face different sets of incentives when considering migration to the United States.

The frequency of legal migration is small in this sample. Less than 2% of the sample is observed having legally made a trip over the period 1987-2000. 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.

Table 1 reports summary statistics of a number of demographic variables for those individuals in the sample. Educational attainment is divided into five categories: Less than 4 years, 4-6 years, 7-9 years, 10-12 years, and 13-16 years. 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 divide communities in the following four sizes, which are, in ascending order: Rancho, Town, Smaller Urban Area, and Metropolitan Area. These categories, although broad, arguably capture community features such as the quality of schools and other public institutions

[9]Empirical evidence suggests that Mexicans entering the U.S. as tourists often do so for the purposes of undocumented labor migration

that may be related to migration behavior. The population is rather evenly distributed across communities of each type, although the Metropolitan category is most frequently observed, accounting for about 32% of the sample.

The Adulthood Cohort variables in Table 1 indicate which year individuals in the sample begin their adult lives as defined in this paper. Table 1 also reports measures of three assets held at the time an individual reached adulthood: hectares of land, properties, and businesses. The Table reports descriptive statistics of these variables, as well as dummy variables indicating whether an individual owned any quantity of these assets at the start of adulthood. Asset ownership at the start of one's adult life is quite low in this sample, although about 6% of the sample reports owning some property at at this time. Along with these Initial Asset variables, Table 1 also reports descriptive statistics for variables measuring migration experience among an individual's immediate family members at the start of an individual's adult life. Around 8% of the individuals report having a father who had gained at least some migration experience by the time that they themselves entered adulthood. Far fewer individuals (2%) reported having a mother who had gained similar experience.

4.1 Observed Patterns of Migration

We 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 the observed number of migratory trips to the U.S. for the whole sample and two subset: those who are observed for less than 10 years in the sample and those observed for 10 or more years. About 28% of individuals in the whole sample have some migration experience, and of these migrants, about 30% are observed taking 2 or more trips to the

Unites States over the sample period. However, these measures are right-censored and therefore may underestimate both the propensity to migrate and the incidence of repeated migration in the sample. One can see the effect of censoring by looking at these measures separately for those observed for less than 10 years and those observed for more than 10 years. Not only is the fraction of migrants larger in the sub-sample that is observed longer (0.24 vs. 0.31), but the fraction of migrants observed taking two or more trips is larger as well (0.26 vs. 0.32).

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 within the first j periods of adulthood, 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 variables 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 $\{m_i^j\}_{j \in \{2,4,6,8\}}$, δ_i, τ_i, along with $\frac{12\delta_i}{\tau_i}$, a measure of the average trip duration in months. [10] Although 6% of the sample migrated within the first two years of adulthood, this increases to around 18% within the first six years, and then to approximately 23% within the first eight years. 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 0.30, suggesting that the migrants in the sample spend about one 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 mean of the $\frac{12\delta_i}{\tau_i}$ variable indicates that average trip observed in the sample lasts a little over 2 years. However, the large sample standard deviation for this variable suggests that the distribution of average trip durations is heavily skewed to the left in this sample.

Table 3 reports the means of the waiting time variables for different categories of education

[10] It is necessary to multiply $\frac{\delta_i}{\tau_i}$ by 12 to measure average trip duration because the denominator of δ_i represents the number of observed months whereas the denominator of τ_i represents observed years

level and community type, respectively. After 8 years of adulthood, individuals with either $4-6$ or $7-9$ years of education are observed to have the highest rates of emigration rate in the sample (approximately 0.25 for both groups) while those with less than 3 years of education have the lowest rate (0.16). Measured at any point within the first decade of adulthood, individuals having $7-9$ years of education seem to have rates of migration which are higher than those exhibited by the groups with the lowest and highest levels of education, although the small sample sizes for the lowest and highest groups make it difficult to draw firm conclusions. Turning our attention to the waiting time variables conditioned on community type, Table 3 reveals that, after 8 years of adulthood, individuals living in Ranchos and Small Urban areas tend to have the highest rates of migration at nearly every point in the first decade of adulthood. Individuals from Metropolitan areas, on the other hand, tend to have the lowest migration rates.

Table 4 reports the means and standard deviations (in parentheses) of the variables describing the pattern of migration, conditional on education and community type. These measures are only taken with respect to the 324 migrants in the sample. Education seems to be related monotonically to both the fraction of time one spends in the U.S., δ_i, as well as the average trip length variable, although the means of both variables fall moving from the $10-12$ Years category to the $13-16$ Years category. There appears to be little variation in the mean of τ_i across community types, but individuals from Towns and Metropolitan Areas are observed taking longer trips to the U.S., which is reflected in the higher average values of δ_i in these groups.

To more precisely investigate the influence of education and community type on the pattern of migration variables, Table 5 reports the results of regressing δ_i, τ_i, and $\frac{12\delta_i}{\tau_i}$ on categorical variables measuring years of education, community type, and adulthood cohort. For δ_i, τ_i, Table 5 reports the results of a Tobit model using data from all individuals in the sample, while for $\frac{12\delta_i}{\tau_i}$, the Table reports OLS regression results using only the migrants in the sample. For each variable, the second column reports results obtained when controls are added for the year of adulthood. Neither education nor community type seems to be significantly related to the average trip duration variable, $\frac{12\delta_i}{\tau_i}$, although this may be a consequence of the relatively small number of migrants in the sample.

Individuals from Towns and Metropolitan Areas tend to have the lowest observed levels of δ_i and τ_i.

The regression results appear to support the existence of a hump-shaped relationship between education and the pattern variables δ_i and τ_i. Both the average fraction of one's life spent in the U.S. and the average number of trips appear to increase as education increases from very low levels to the 4-6 Years and 7-9 Years categories. These measures reach a peak for individuals in the group with 7-9 Years of education and then decline as education increases beyond that level. These results uncover a pattern consistent with the results of studies such as Chiquiar and Hanson (2005) that find intermediate selection among migrants. Here however, we not only see evidence of intermediate selection into migration, as borne out by Table 3, but also intermediate selection into patterns of migration that involve taking more trips to the U.S. and spending more time abroad, as revealed by Table 4 and the regression results in Table 5. Since we do not observe preferences or the complete costs of migration, reduced-form methods cannot help us to identify the underlying source of these patterns of intermediate selection. However, by imposing our model on the data, and estimating its structural parameters, we may be able to gain insight into how education and community type affect the pattern of migration.

5 Identification and Estimation Strategy

5.1 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. As demonstrated in the Appendix, 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 below, the wage data that are available through the MMP permit the estimation of wage distributions in both Mexico and the United States. Given these wage distributions, 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, σ_λ, along with the initial capital stock, k_1, 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.[11] 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 3 displays level curves for the average value of τ_i when the model is simulated 500 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 increase 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 3 displays level curves for the average value of δ_i when the model is simulated 500 times for different combinations of μ_η and μ_λ. Panel 3 of Figure 3 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 parameters σ_η and σ_λ are then related to the variances of both δ_i and τ_i. A particular set of expected values for δ_i^2, and τ_i^2 may therefore identify σ_η and σ_λ.

The $\{m_i^j\}_{j\in\{2,4,6,8\}}$ variables contain information on the average waiting time until first migration, along with overall migration rate in the population. For migrants who begin life with low levels of assets, the time until first migration is determined by the cost of migration, the home wage distribution, and the initial stock of assets, k_1. Given that we can independently identify the home

[11]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.

wage distribution and the cost of migration, the expected values of the waiting time parameters $\{m_i^j\}_{j \in \{2,4,6,8\}}$ allow us to identify the initial level of assets, k_1.

5.2 The Empirical Model

One can overcome the lack of complete wage and asset data by using the wage data that is available from the MMP to estimate the U.S. and Mexican wage distributions and then generate a number of simulated migration-life histories for each individual. For each simulation, optimal migration behavior and the evolution of k_t can be determined by a set of initial conditions, a sequence of random draws from estimated wage distributions, and the optimal behavior implied by the solution to the structural model. One can then estimate the parameters of the structural model using the Method of Simulated Moments. This process entails finding the parameters that generate values of a selected set of sample moments in a simulated population that most closely match those found in the observed sample. Before describing the estimation procedure in more detail, let us first fully specify the empirical model.

In constructing the theoretical model, I have assumed a finite horizon. I follow Colussi (2006) in assuming that one's life as an adult worker ends at the start of age 65. Let a_i^{adult} represent the age at which individual i is considered as an adult in our sample. This means that, for the purposes of estimation, individual i is assumed to possess a finite horizon of $y_i^o = (65 - a_i^{adult})$ years, where y_i^o represents the number of years that individual i is observed in the sample. However, since the data on time spent in the U.S. is measured in months, a finer measurement of time is desirable when applying the model to the data. Hence, I take each unit of time in the model to be a six month period, so that an individual with a 50 year horizon has a lifetime of 100 periods in the model, and is observed making location decisions for $2y_i^o$ periods.

Let variables of the type $EDU_{i,j}$ constitute a set of categorical variables indicating whether or not individual i has attained the j^{th} level of schooling, where the j values $[1, 2, 3, 4]$ correspond to the following educational ranges: [4-6 Years,7-9 Years, 10-12 Years, 13-16 years]. The educational range 0-3 Years is excluded as a reference category. Similarly, let variables of the type $COM_{i,m}$ indicate whether or not individual i comes from a community of type m, where the m values [T,SU,M] correspond to community types [Town, Small Urban, Metropolitan]. The Rancho community type is excluded as a reference category.

The cost of migration for individual i, $\lambda_{i,t}$, is partly determined by individual characteristics and partly determined by environmental forces such as border enforcement policy in the United States. The cost of migration that an individual i faces in period t is then modeled as:

$$\lambda_{i,t} = \overline{\gamma}^{\lambda} + \sum_{j} \gamma^{\lambda}_{e,j} EDU_{i,j} + \sum_{m} \gamma^{\lambda}_{c,m} COM_{i,m} + \gamma^{\lambda}_{b} B_t \tag{11}$$

Here $\overline{\gamma}^{\lambda}$ is a constant term, and B_t represents a measure of the intensity of enforcement along the US-Mexican border in year t. We measure B_t 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. The top panel of Figure 4 presents a plot of this variable over the period 1986-2005. The growth rate of the payroll increases significantly after 1995, perhaps reflecting a U.S. policy response to the Mexican Peso Crisis. [12] Let the full vector of parameters associated with the cost of migration be denoted by $\overrightarrow{\gamma^{\lambda}}$.

The location preference shock, $\eta_{i,t}$, is modeled as follows:

$$\eta_{i,t} = \overline{\gamma}^{\eta} + \sum_{j} \gamma^{\eta}_{e,j} EDU_{i,j} + \sum_{m} \gamma^{\eta}_{c,m} COM_{i,m} + \varepsilon^{\eta}_{i,t} \tag{12}$$

The random components $\varepsilon_{i,t}$ are assumed to be identically and independently across individuals and time periods as: $\varepsilon^{\eta}_{i,t} \sim N(0, \sigma^2_{\eta})$ where $\sigma_{\eta} = exp(\gamma^{\eta}_{\sigma})$. Let $\overrightarrow{\gamma^{\eta}}$ denote the vector of parameters associated with $\eta_{i,t}$.

We must also account for the initial capital stock, k_1. Although the value of an individual's entire stock of financial assets at any time is unknown, the MMP data on the holdings of different asset classes can be used to uncover variation in initial wealth. All of asset classes described in

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

Table 1 (hectars of land, properties, and businesses) could be used to model the value of the initial asset stock. However, given that ownership of land and businesses at the start of adulthood is very rare in our sample, only the ownership of property variable is used. Let the dummy variable, P_i signal initial ownership of a property. The migration experience of an individual's father at the start of adulthood may also affect the initial asset stock. If migration reflects greater family resources or generates more family wealth, then those individuals with a migrant father at the start of adulthood might have a greater starting asset stock. Let FM_i represent a dummy variable indicating whether or not an individual's father had any migration experience before or during the first year that an individual i reached adulthood. The initial asset stock, $k_{i,1}$ is then modeled as:

$$k_{i,1} = exp(\overline{\gamma}^k) + \gamma_p^k P_i + \gamma_{fm}^k FM_i \tag{13}$$

Let $\overrightarrow{\gamma^k}$ denote the vector of parameters associated with $k_{i,1}^h$.

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 4 displays the time trend of B_t over the time frame of the sample. The bottom panel of this figure also plots the real exchange rate, measured over six month intervals, for the period 1987-2005. This series is constructed using quarterly data on the exchange rate and the CPI in Mexico and the U.S. from the IMF's September 2007 release of *International Financial 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 time trend equations using OLS:

$$\log(B_t) = \gamma_0^B + \gamma_1^B Trend_t + \gamma_2^B Trend_t^2 + \gamma_3^B Crash_t + \gamma_4^B Trend_t * Crash_t + \gamma_5^B Trend_t^2 * Crash_t + \varepsilon_t^B \quad (14)$$

$$\log(ex_t) = \gamma_0^{ex} + \gamma_1^{ex} HTrend_t + \gamma_2^{ex} HTrend_t^{-1} + \gamma_3^{ex} Crash_t + \gamma_4^{ex} HTrend_t * Crash_t + \gamma_5^{ex} HTrend^{-1} * Crash_t + \varepsilon_t^{ex} \quad (15)$$

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 $\varepsilon_t^{ex} \sim N(0, \sigma_{ex}^2)$. $Crash_t$ has been added as a dummy variable indicating years or half 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.

The B_t data are recorded annually, so t measures years in Equation 14 and the $Trend_t$ variable takes a value of 1 for the year t=1987 and grows by one unit in each successive year. To model expectations about the level of border enforcement on a six-month basis, I estimate Equation 14 using the annual data and interpolate between years. On the other hand, the real exchange rate is measured every half year, so t measures half-years in Equation 15 and the $HTrend_t$ variable takes a value of 1 during the first half of 1987 and increases by one unit in each successive half year.

Individual expectations about the distributions of B_t and ex_t are assumed to be consistent with OLS estimates of Equations 14 and 15. Before the Peso Crisis, I assume that individuals expect a distribution 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 14 and 15 when $Crash_t = 1$. This type of instantaneous adjustment may abstract from a more realistic environment in which beliefs sluggishly adjust, but it is hoped that 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 September 2007 release of *International Financial Statistics*. This implies $R = 1.0119$ for a six month period. I make a similar simplifying assumption when dealing with ppp_t by setting to its average value over this time-period (0.1689), as derived from OECD data and CPI data for both countries from the IMF.[13]

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

Although the the MMP data do not record wage outcomes for every year in the lives of household heads, they do contain data on wage outcomes and the average number of hours worked per week for each migrant's most recent trip to the United States.[14] After excluding a small number of migrants who failed to find a job on their last trip, I have a sample of 1263 observations on labor income for males working in the U.S. either without documents or as tourists over the period 1987-2000. These data can be used to construct a measure of estimated labor income for a one-month period. The MMP data also record a current measure of the labor incomes of all household heads. Considering only those individuals interviewed Mexico, the MMP data thus yeild 4970 observations of domestic income data with information on the frequency of measurement.

I assume that each period in the structural model represents six months. Therefore, I use the MMP income data to model real income earned in the U.S. and Mexico over a six month period of

[13]The OECD series for ppp_t can be found at http://www.oecd.org/dataoecd/61/56/1876133.xls

[14]These data include observations on both household heads and non-household heads, so the data used here include individuals that are not included in the main sample of this paper.

time as functions of age, the square of age, education, an individual's community type, and a time trend variable, $Trend_t$:[15]

$$\log(w_t^{US}) = \gamma_{w,0}^{US} + \sum_j \gamma_{e,j}^{US} EDU_{i,j} + \sum_m \gamma_{c,m}^{US} COM_{i,m} + \gamma_T^{US} Trend_t + \varepsilon_{i,t}^{US} \quad (16)$$

$$\log(w_t^{MEX}) = \gamma_{w,0}^{MEX} + \sum_j \gamma_{e,j}^{MEX} EDU_{i,j} + \sum_m \gamma_{c,m}^{MEX} COM_{i,m} + \gamma_T^{MEX} Trend_t + \gamma_{cr}^{MEX} Crash_t + \gamma_{crT}^{MEX} Trend * Crash_t + \varepsilon_{i,t}^{MEX} \quad (17)$$

For the Mexican wage regression, a dummy variable $Crash_t$ has been added indicating years since the Peso crisis of 1995 to capture the fall in Mexican real wages following that event. The interaction term $Trend_t * Crash_t$ allows the time trend in Mexican wages to be affected by the Peso crisis. The wage shocks $\varepsilon_{i,t}^{US}$ and $\varepsilon_{i,t}^{MEX}$ are assumed to be independently and identically distributed across years and individuals, but the inclusion of the $Trend_t$ and $Crash_t$ terms in the wage equations implies that the deterministic components of the wage distributions vary across time.

Table 6 presents results from the two-step efficient GMM estimation of Equations 16 and 17.[16]Monthly earnings are calculated in real dollars or pesos using CPI measures for Mexico and the U.S. from the IMF's March 2007 release of *International Financial Statistics*. The year 2000 is taken to be the base year. The estimation results for Mexican wages present a reasonable age-income profile, and the coefficient estimates on the education dummy variables suggest the expected positive relationship between education and income. There does not appear to be significant differences in the labor income of individuals from Ranchos, Towns, and Small Urban Areas. However, labor incomes in Metropolitan Areas are significantly higher than those in Ranchos (approximately 18% higher). Before the Peso crisis, labor incomes were declining, and they experienced a severe drop in the immediate aftermath of the crisis. However, the estimated coefficient on $Trend_t * Crash_t$ indicates that labor incomes started to climb after the crisis.

The estimation results for U.S. wages offer a few surprising results. Age is not found to be

[15]We compute real monthly earnings and then multiply this variable by six before taking logs to generate the dependent variable.

[16]GMM is used instead of OLS 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 GMM framework.

significantly related to labor income. Although this stands in stark contrast to typical results, this may be explained if migrants in the U.S. tend to find jobs where physical strength and stamina are highly related to productivity. This might be the case in most agricultural jobs as well as in 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 estimates 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 lower in the U.S. than in Mexico. Community type does not appear to exert a significant effect on income.

Individuals are assumed to have beliefs about the wage distributions that are consistent with the parameter estimates for Equations 16-17. 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 $Trend_t = 14$ 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 17 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 17 when $Crash_t = 1$. Table 7 provides a summary of the complete empirical model.

5.3 Estimation

The estimation procedure followed here relies on the Method of Simulated Moments. Rather than trying to model each location decision made by the individuals in the sample, 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 characterize the pattern of migration for an individual. Let $\mathfrak{p}_i$ represent a vector of observed variables characterizing individual $i's$ pattern of migration:

$$\mathfrak{p}_i = [m_i^2, m_i^4, m_i^6, m_i^8, m_i^{10}, \delta_i, \delta_i^2, \tau_i, \tau_i^2] \tag{18}$$

The $\mathfrak{p}_i$ vector contains the pattern variables defined earlier as well as the squares of δ_i and τ_i to pick up information about the dispersion of these two variables. Next, let X_i represent the following vector of individual characteristics, along with a constant:

$$\begin{aligned} X_i &= [1, EDU_{i,2}, EDU_{i,3}, EDU_{i,4}, EDU_{i,5}, COM_{i,T}, COM_{i,SU}, COM_{i,M} \\ &\quad 1(y_i^{adult} \in \{1989, 1990\}), 1(y_i^{adult} \in \{1991, 1992, 1993\})] \end{aligned} \tag{19}$$

Where $1(\cdot)$ represents an indicator function taking a value of 1 if the argument is true and 0 otherwise. Then $\mathfrak{p}_i \otimes X_i$ represents a vector of observables recording the pattern of migration of a particular individual i in a form that will allow us to record the average values of these observables across the different characteristic groups defined by X_i.

Now, let Π^M refer to the vector of migration parameters in the structural model: $\Pi^M = \{\overrightarrow{\gamma}^k, \overrightarrow{\gamma}^\lambda, \overrightarrow{\gamma}^\eta\}$ Furthermore, let Π^w refer to the vector of wage parameters estimated from the labor income data: $\Pi^w = \{\overrightarrow{\gamma}^{US}, \overrightarrow{\gamma}^{MEX}\}$. For a given pair of Π^M and Π^w, I approximate the value functions for each individual given their characteristics and their year of adulthood, and I also generate a vector of ρ draws for each of the three disturbance terms: $\varepsilon_{i,t}^{\eta}$, $\varepsilon_{i,t}^{Mex}$, and $\varepsilon_{i,t}^{US}$. [17] For each individual i, these vectors have length equal to $2y_i^o$. For 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 $\widetilde{\mathfrak{p}_{i,j}}(\Pi^M, \Pi^w)$ 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

[17] To construct these random vectors, we first start with three $2y_i^o \times \rho$ 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.

represents the vector of moment conditions used in the estimation procedure:

$$g(\mathfrak{p}_i, X_i, \Pi^M, \Pi^w) = \left[\mathfrak{p}_i \otimes X_i - \frac{1}{\rho} \sum_{j=1}^{\rho} \widetilde{\mathfrak{p}}_{i,j}(\Pi^M, \Pi^w) \otimes X_i \right] \tag{20}$$

The Method of Simulated Moments Estimator for Π is then given by:

$$\Pi^*_{MSM} = ArgMin_{\Pi^M} \ [\frac{1}{n} \sum_{i=1}^{n} g(\mathfrak{p}_i, X_i, \Pi^M, \Pi^w)] W [\frac{1}{n} \sum_{i=1}^{n} g(\mathfrak{p}_i, X_i, \Pi^M, \Pi^w)]' \tag{21}$$

Where W is a positive semi-definite matrix weighting the moment conditions. Due to computational requirements of the estimation procedure, all estimates reported here have been obtained by setting W equal to the identity matrix.[18]

6 Estimation Results

Table 8 presents estimation results for two specifications of the structural model.[19] All reported standard errors are computed using the expansion method described in the Appendix. In Column I of Table 8, we momentarily ignore the influence of education and community type on $\eta_{i,t}$ and $\lambda_{i,t}$ and assume that the mean values of these variables are the same for all individuals.[20] The estimated value of -0.76 for $\overline{\gamma}^{\eta}$ suggests a preference for residence in the home country. Turning to the parameter estimates for the initial condition, we see that the average level of initial assets is estimated to be economically insignificant (less than 1000 real pesos). Possessing a property and having a father with migration experience at the time of adulthood are estimated to add about 78,000 and 160,000 real pesos (year 2000) on average to an individual's initial asset stock.

Given the specification of column I in Table 8, we estimate γ_b^{λ}, the coefficient on the intensity

[18] I plan to obtain future estimates using a two-step procedure that utilizes an estimate of the efficient weighting matrix.

[19] Column I fixes μ_η and μ_λ across education and community groups while Columns II reports results when these parameters are allowed to vary by education groups. Future versions of this paper will report estimates when these parameters are allowed to vary by community groups as well.

[20] This version of the paper does not include estimation results that allow $\eta_{i,t}$ and $\lambda_{i,t}$ to vary by community type. Estimation of the parameters in this case is in progress.

of border enforcement in the migration cost distribution, to be 0.56. This estimate suggests that a 10% rise in the intensity of border enforcement is expected to increase the cost of migration by about 5.6%. The expansion of border enforcement activities over the period 1987-2000 appears to have indeed reduced the ease of crossing the U.S. border without documents.

Column II of Table 8 provides structural parameters estimates when the means of the location preference term and the cost of migration are allowed to vary by education. None of the coefficients on specific educational group variables are found to be statistically significant. This prevents us from drawing strong conclusions from the point estimates and instead suggests that the differences in migration behavior observed across different educational groups are primarily driven by differences in mean wages. Taking the point estimates at face value, the results generally suggest that the disutility associated with being in the United States declines (becomes smaller in magnitude) as education increases, although the least educated group (the excluded group) is not found to have the most intense disutility from time spent away from home. This pattern may be explained if more educated individuals have an easier time operating in American society, perhaps because of higher rates of English fluency or because they are generally more cosmopolitan than less educated individuals. The parameters related to the cost of migration in Column II of Table 8 are also found to be statistically insignificant. The point estimates suggest that individuals with 4-6 years of education and those with 13-16 years of education have lower costs of migration, but there does not seem to be a firm pattern in the point estimates.

To assess how well the model explains the data, it is useful to compare the empirical means of some of the summary statistics used to form moment conditions with their simulated counterparts given the parameter estimates in Column II of Table 8. Table 9 compares the means of these variables for the complete sample and also for sub-samples sharing the same level of schooling. The first panel suggests that the model does an excellent job of predicting the migration rates in the population observed at different intervals after the start of adulthood (as measured by the m_i^j variables). The model predicts a slightly higher value of δ_i (the fraction of life spent in the U.S.) than what is observed in the whole sample, and a slightly lower value of τ_i (the average number of trips per year) in the whole sample. Looking at the fit of the model across different educational groups, the model does a relatively poor job of matching the migration profile suggested by the m_i^j variables for individuals with 13-16 years of education.

As discussed earlier, the estimation results suggest that the intensity of border enforcement is positively related to the cost of migration. In order to more carefully assess the effects of U.S. border enforcement, the parameter estimates will now be used to simulate the behavior of the individuals in the sample under various counterfactual policy regimes. Over the period 1986-2005, the Border Patrol's Souther Sector experienced an average six-month growth rate of approximately 4%. How would the individuals in the sample have behaved had they been exposed to a different policy regime? To answer this question, we can use the parameter estimates from Column II of Table 8 to simulate the behavior of the sample under different Border Patrol payroll growth rates. Figure 5 presents sample averages of the migration pattern variables for simulated populations exposed to different constant growth rates of border enforcement over the period 1987-2000. All points are derived by simulating the model 500 times per person. In all simulations, it is assumed that individuals correctly anticipate the trend of payroll expansion and expect zero-mean shocks around this trend with the same variance observed in the empirical payroll data.

Panel 1 of Figure 5 reveals that as the growth rate of the Border Patrol payroll increases, the average levels of both δ_i, the fraction of one's life spent in the U.S. and τ_i, the average number of trips per year, decline. This is consistent with theoretical expectations. As the cost of migration increases, individuals take fewer trips to the United States, and must wait in Mexico longer before accumulating assets sufficient to migrate. Panel 2 of Figure 5 confirms this pattern, as the averages of the m_i^j variables all decline as the growth rate of border enforcement increases. The simulation results are therefore inconsistent with argument described earlier that the expansion of Border Patrol activity over the last twenty years is responsible for the increasing population of undocumented migrants. Instead, the model and parameter estimates suggest that if the growth rate of border enforcement had been lower over the last two decades, individuals in Mexico would have migrated with greater frequency, spending larger fractions of their lives in the United States.

7 Conclusion

The model developed here advances the literature on circular migration by considering an environment in which individuals can take multiple migratory trips and save assets. The model explains repeated circular migration as arising from a combination of the international wage gap, a preference for residence in one's home country, and an imbalance between the real exchange rate and the rate of purchasing power parity between the home and foreign countries. Estimates of the structural parameters, derived using Mexican Migrant Project Data, shed some light on the effect of border enforcement and education on migration behavior. One of the key empirical results is that the intensity of border enforcement, as measured by the size of the Border Patrol's Southern payroll, is positively related to the cost of migration. Counterfactual experiments predict that border policies involving higher growth rates of the Border Patrol payroll would be associated with lower rates of undocumented migration, and would cause migrants to spend smaller fractions of their lives in the United States.

The MMP data indicate that the pattern of circular migration exhibited by individuals varies with schooling. Individuals possessing intermediate levels of education are found to spend a greater fraction of their lives in the United States and take trips at a faster rate than other groups. The structural parameter estimates generally do not support the hypothesis that variation in location preferences and migration costs across education groups explain this pattern. It appears that differences in wages across education groups drive the observed differences in migration behavior.

Future research can use this model and the parameter estimates found here to conduct policy experiments that would be otherwise impossible to perform. The expansion of the undocumented population in the United States has led to numerous calls for the enactment of expanded guest-worker programs. The intent of these programs is to offer Mexican workers a legal alternative to undocumented migration. The model and parameter estimates presented here could be used to assess whether individuals would be willing to participate in these programs, and how these programs would alter the selectivity of Mexican migration. Since the selectivity of undocumented migrants often plays a central role in debates about U.S. migration policy, such experiments can shed light on important consequences of proposed guestworker programs.

In estimating the model, I have ignored the presence of unobserved individual heterogeneity in wage distributions and the distributions of the location preference shock and the cost of migration. A task for future research is to account for such heterogeneity in the estimation of the model. Additionally, I have only considered the influence of education and community type on the structural parameters. Future work should account for the effects of important demographic variables such as marital status and the number of children. These family variables may exert a significant role on the desirability of residence in Mexico, but I have not included them in the present analysis to simplify the solution and estimation of the model.

A Appendix

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:

$$E_{\Omega^h_{t+1}}\left[V^h_{t+1}(k^h_{t+1}|\Omega^h_{t+1})\right] = \int_0^\infty \int_0^\infty \int_0^\infty \Big[V^h_{t+1}(k^h_{t+1}|\{w^h_{t+1}, \lambda_{t+1}, ex_{t+1}\})* \\ f_{w^h}(w^h_{t+1}) f_\lambda(\lambda_{t+1}) f_{ex_{t+1}}(ex_{t+1})\Big] dw^h_{t+1} d\lambda_{t+1} dex_{t+1} \quad (22)$$

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 22 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:

$$\chi_i = \frac{\int_{x_i^{-1}}^{x_{i+1}^{-1}} x f_x(x) dx}{F_x(x_{i+1}^{-1}) - F_x(x_i^{-1})} \tag{23}$$

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:

$$\int_{-\infty}^{\infty} x f_x(x) dx \approx \frac{1}{n} \sum_{i=1}^{n} \chi_i \tag{24}$$

Returning to the example in 22, let $\widetilde{w_{t,i}^h}$, $\widetilde{\lambda_{t,j}}$, 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 $E_{\Omega_{t+1}^h}\left[V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right]$ may be approximated as:

$$E_{\Omega_{t+1}^h}\left[V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right] \approx \frac{1}{n^3} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} V_{t+1}^h(k_{t+1}|\{\widetilde{w_{t,i}^h}, \widetilde{\lambda_{t,j}}, \widetilde{ex_{t,k}}\}) \tag{25}$$

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

A.2 Value Function Approximation Using the Method of Endogenous Gridpoints

A complete solution to the model presented here requires solving or approximating the value functions $\nu_t^{hh}(k_t|\Omega_t^h)$, $\nu_t^{hf}(k_t|\Omega_t^h)$, $\nu_t^{fh}(k_t|\Omega_t^f)$ and $\nu_t^{ff}(k_t|\Omega_t^f)$ for each t. This may be accomplished using approximations of two value functions that can be modified to encompass all of these functions.

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 $\mathfrak{v}_t^h(\omega_t)$ as follows:

$$\begin{aligned} \mathfrak{v}_t^h(\omega_t) &= E_{\Omega_{t+1}^h}\left[\max_{\mathcal{C}_{h,t}} \log(\mathcal{C}_{h,t}) + \beta V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right] \\ & s.t.\ k_{t+1} = R[\omega_t - \mathcal{C}_{h,t}] \\ & \mathcal{C}_{h,t} \leq \omega_t \end{aligned} \tag{26}$$

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

Suppose that we can evaluate $E_{\Omega_{t+1}^h}\left[\beta V_{t+1}^h(k_{t+1}^h|\Omega_{t+1}^h)\right]$, 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 26 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 $\mathfrak{v}_t^h(\omega_t)$ from $\overrightarrow{\omega}$ and $\overrightarrow{\mathfrak{v}^h}$.

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 26 for each interpolation node. In order to avoid the computational expense associated with traditional interpolation methods, we approximate the value function in Equation 26 using the method of endogenous gridpoints developed by Carroll (2006). Instead of starting with an exogenous vector of interpolation nodes for wealth at the beginning of the period, $\overrightarrow{\omega}$, we start with an exogenous vector of nodes for k_{t+1}, the level of assets at the end of the period: $\overrightarrow{k} = [k^1, k^2, ...k^i, ...k^n]$. We know that each of these end-of-period asset nodes k^i would result if the worker began the period with some initial level of wealth, ω_E^i, and chose a corresponding optimal level of consumption, $\mathcal{C}_{h,t}^i$. Assuming an interior solution, the optimal level of consumption that solves the problem in

Equation 26 and results in end-of-period assets k^i satisfies the following first order condition:

$$\frac{1}{\mathcal{C}_{h,t}^i} = R\beta \left[\partial E_{\Omega_{t+1}^h}\left[\beta V_{t+1}^h(k_{t+1}^h|\Omega_{t+1}^h)\right]/\partial k_{t+1}\right] \tag{27}$$

If $\mathcal{C}_{h,t}^i$ is optimal and results in end-of-period assets $k_{t+1} = k^i$, then it must be the case that the worker began the period with the wealth level ω_E^i that satisfies:

$$k^i = R[\omega_E^i - \mathcal{C}_{h,t}^i] \tag{28}$$

Where the subscript E on ω_E^i notes that this node of initial wealth has been endogenously determined from the exogenous node k^i and the solution to Equation 26.

For each k^i in $\overrightarrow{k}$, we calculate the values ω_E^i and $\mathcal{C}_{h,t}^i$ that yield k^i as the optimal level of end-of-period assets. This generates a vector of endogenously determined start-of-period wealth nodes, $\overrightarrow{\omega_E}$ with a corresponding vector of function values $\overrightarrow{\mathfrak{v}^h}$ with elements determined by:

$$\mathfrak{v}^{h,i} = \log(\mathcal{C}_{h,t}^i) + \beta E_{\Omega_{t+1}^h}\left[\beta V_{t+1}^h(k^i|\Omega_{t+1}^h)\right] \tag{29}$$

We then use piece-wise linear splines to approximate $\mathfrak{v}_t^h(\omega_t)$ by interpolation using $\overrightarrow{\omega_E}$ and the corresponding values $\overrightarrow{\mathfrak{v}^h}$. This procedure results in efficiency gains relative to conventional methods because it requires fewer operations to compute $\mathcal{C}_{h,t}^i$, ω_E^i, and $\mathfrak{v}^{h,i}$ from Equations 27- 29 than to numerically solve the optimization problem in Equation 26.

One complication that arises in applying the method of endogenous gridpoints to this model is that the function $E_{\Omega_{t+1}^h}\left[\beta V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right]$ is not strictly concave, but instead has both convex and concave sections. Although the function starts out concave at low levels of k_{t+1}, it becomes convex as k_{t+1} starts approaching the expected value of λ_{t+1}. The marginal value of assets increases because, at low asset levels, increases in the asset stock increase the probability that the worker will be able to afford migration. However, for sufficiently high levels of k_{t+1}, the function again displays concavity. Since the first derivative of $E_{\Omega_{t+1}^h}\left[\beta V_{t+1}^h(k_{t+1}|\Omega_{t+1}^h)\right]$ with respect to k_{t+1} is not monotonic, then for a given level of start-of-period wealth, ω^i, multiple feasible consumption levels may satisfy the first order condition given in Equation 27, even though there is only one optimum. Therefore, applying the above method can sometimes result in an incorrect calculation of the $\mathfrak{v}^{h,i}$ associated with a particular ω_E^i. In practice it has been observed that when this error occurs, it results in vectors $\overrightarrow{\omega^E}$ and $\overrightarrow{\mathfrak{v}^h}$ that suggest non-monotonicity in the value function. We correct for this by generating $\overrightarrow{\omega_E}$ and $\overrightarrow{\mathfrak{v}^h}$ as described above and then checking if these vectors suggest non-monotonicity at any particular node ω_E^i. If there is a non-monotonicity at ω_E^i, we calculate $\mathfrak{v}_t^h(\omega_E^i)$ using a numerical optimization algorithm and replace $\mathfrak{v}^{h,i}$ with the resulting value. We then check the nodes immediately before and after ω_E^i in $\overrightarrow{\omega_E}$, calculating $\mathfrak{v}_t^h(\omega_E^i)$ using a numerical optimization algorithm and replacing their corresponding $\mathfrak{v}^{h,i}$ values if the differences between these values and the newly calculated values are non-negligible. We continue checking the surrounding nodes in either direction until we reach a node with a corresponding value in the $\overrightarrow{\mathfrak{v}^h}$ that is found to be accurate.

The value functions $\nu_t^{hf}(k_t|\Omega_t^h)$ and $\nu_t^{ff}(k_t|\Omega_t^h)$ can be approximated by first approximating the value function $\mathfrak{v}_t^f(\omega_t)$, defined as:

$$\begin{aligned} \mathfrak{v}_t^f(\omega_t) \quad &= \quad E_{\Omega_{t+1}^f}\left[\max_{\mathcal{C}_{f,t}} \log\left(\frac{\mathcal{C}_{f,t}}{ppp}\right) + \beta V_{t+1}^f(k_{t+1}|\Omega_{t+1}^h)\right] \\ & \quad\quad s.t.\ k_{t+1} = R[\omega_t - ex_t\mathcal{C}_{f,t}] \\ & \quad\quad \mathcal{C}_{f,t} \leq \frac{\omega_t}{ex_t} \end{aligned} \tag{30}$$

Approximation of $\mathfrak{v}_t^f(\omega_t)$ is sufficient because $\nu_t^{hf}(k_t|\Omega_t^h) = E_{w_t^f,\eta_t}\left[\eta_t + \mathfrak{v}_t^f(k_t + ex_t(w_t^f - \lambda_t))\right]$ and $\nu_t^{ff}(k_t|\Omega_t^h) = \eta_t + \mathfrak{v}_t^f(k_t + w_t^f)$. However, we cannot apply exactly the same approximation method to this function as we did for $\mathfrak{v}_t^h(\omega_t)$ 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 $\widehat{\mathfrak{v}}_t^f(\omega_t)$ as follows:

$$\widehat{\mathfrak{v}}_t^f(\omega_t) = E_{\Omega_{t+1}^f}\left[\max_{\widehat{\mathcal{C}}_{f,t}} \log\left(\frac{\widehat{\mathcal{C}}_{f,t}}{ppp}\right) + \beta V_{t+1}^f(k_{t+1}|\Omega_{t+1}^h)\right] \tag{31}$$
$$s.t.\ k_{t+1} = R[\omega_t - \widehat{\mathcal{C}}_{f,t}]$$
$$\widehat{\mathcal{C}}_{f,t} \leq \omega_t$$

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

I approximate $\widehat{\mathfrak{v}}_t^f(\omega_t)$ using the method of endogenous gridpoints and use this approximation to approximate $\nu_t^{hf}(k_t|\Omega_t^h)$ and $\nu_t^{ff}(k_t|\Omega_t^h)$. Once we have approximations of the value functions $\nu_t^{hh}(k_t|\Omega_t^h)$, $\nu_t^{hf}(k_t|\Omega_t^h)$, $\nu_t^{fh}(k_t|\Omega_t^f)$ and $\nu_t^{ff}(k_t|\Omega_t^f)$ for a given period, we can use these to approximate $E_{\Omega_t^h}\left[\beta V_{t+1}^h(k_t|\Omega_t^h)\right]$ $E_{\Omega_t^f}\left[\beta V_{t+1}^f(k_t|\Omega_t^h)\right]$ using conventional interpolation methods.

A.3 Identification with Full Information

If a number of individuals are observed in the final period of life, and with full information on assets and wages each period, one can identify the behavioral parameters of the model (μ_η,σ_η,μ_λ,σ_λ). Let us assume that data on observed wages could be used to identify the parameters of the wage distributions in the U.S. and Mexico. The outmigration and return migration probabilities in period $t = T$ are given by:

$$Prob(L_T = 1 \mid L_{T-1} = 1) = Prob\left(\eta_t > -log\left(\frac{\frac{k_T}{ex_T} + w_T^f}{ppp}\right) + E_{w^h}[log\left(k_T + w_T^f\right)]\right) \tag{32}$$
$$= 1 - \Phi\left(\frac{1}{\sigma_\eta}\left(-\mu_\eta - log\left(\frac{\frac{k_T}{ex_T} + w_T^f}{ppp}\right) + E_{w^h}[log(k_T + w_T^f)]\right)\right) \tag{33}$$
$$Prob(L_T = 1 \mid L_{T-1} = 0) = Prob\left(\frac{k_T}{ex_T} > \lambda_T\right) Prob\left(\mu_\eta + E_{w^f}\left[log\left(\frac{\frac{k_T}{ex_T} - \lambda_t + w_T^f}{ppp}\right)\right] > log(k_T + w_T^h) \mid \frac{k_T}{ex_T} > \lambda_T\right) \tag{34}$$
$$\approx \Phi\left(\frac{1}{\sigma_\lambda}\left(-\mu_\lambda + log\left(\frac{k_T}{ex_T}\right)\right)\right) \times \Phi\left(\frac{1}{\sigma_\lambda}\left(-\mu_\lambda + log\left(\frac{k_T}{ex_T}\right) + log(\Upsilon) \mid log\left(\frac{k_T}{ex_T}\right) > log(\lambda_T)\right)\right) \tag{35}$$

Where $\Upsilon = \left(\mu_\eta + log\left(\frac{1}{ppp}\left(\frac{k_T}{ex_T}\right)\right) + \frac{ex_T}{k_T}E[w_T^f] - log(k_T + w_T^h)\right)$. With full-information, one could estimate Equation 33 using a traditional Probit model with the following two linear regressors: a constant term, and $(-log((k_T + w_T^f)/ppp)) + E_{w^h}[log(k_T + w_T^f)])$. There are two unknown or unidentified parameters in this equation: μ_η, and σ_η. The coefficient on the $(-log((k_T + w_T^f)/ppp)) + E_{w^h}[log(k_T + w_T^f)])$ term would uniquely identify σ_η, while one could solve for an estimate of μ_η given the estimated constant and the estimated value of σ_η. Turning to the last-period outmigration decision, Equation 35, we see that the probability of outmigration is the product of the probability that an individual can afford migration and the probability that migration is desirable, given that it is affordable.[21] In estimating Equation 35, we could model the argument in the first cdf function has having a constant term and one additional linear regressor: $log\left(\frac{k_T}{ex_T}\right)$. The argument in the second cdf function could be modeled as a linear function of a constant term and one additional regressor: $\left(log\left(\frac{k_T}{ex_T}\right) + log(\Upsilon)\right)$. There are two parameters left to be identified: μ_λ and σ_λ. The estimated coefficients on the non-constant regressors in the two cdfs of Equation 35 identify σ_λ, while the estimated coefficients on the constant terms in the two cdfs identify μ_λ.

Even without data on period T behavior, one can still identify the parameters of the model given complete wage and asset data. Let $\nu_t^{ff\,-}(k_t|\Omega_t^f) = (\nu_t^{ff}(k_t|\Omega_t^f) - \eta_t)$. For any period, t, the probabilities of outmigration and return migration in each period are then given by:

$$\begin{aligned}
Prob(L_t = 1 \mid L_{t-1} = 1) &= Prob\left(\eta_t > -\nu_t^{ff\,-}(k_t|\Omega_t^f) + \nu_t^{fh}(k_t|\Omega_t^f)\right) \\
&= 1 - \Phi\left(\frac{1}{\sigma_\eta}(-\mu_\eta - \nu_t^{ff\,-}(k_t|\Omega_t^f) + \nu_t^{fh}(k_t|\Omega_t^f))\right) \qquad (36) \\
Prob(L_t = 1 \mid L_{t-1} = 0) &= Prob\left(\frac{k_t}{ex_t} > \lambda_t\right) Prob\left(\nu_t^{hf}(k_t|\Omega_t^h) > \nu_t^{hh}(k_t|\Omega_t^h) \mid \frac{k_t}{ex_t} > \lambda_t\right) \\
&= \Phi\left(\frac{1}{\sigma_\lambda}\left(-\mu_\lambda + log\left(\frac{k_t}{ex_t}\right)\right)\right) \times \\
&\quad Prob\left(\nu_t^{hf}(k_t|\Omega_t^h) > \nu_t^{hh}(k_t|\Omega_t^h) \mid \frac{k_t}{ex_t} > \lambda_t\right) \qquad (37)
\end{aligned}$$

[21] Note that in deriving Equation 35 from Equation , the following approximation was applied: $log(1 + \frac{w_T^f - \lambda_T}{ex_T/k_T}) \approx (\frac{w_T^f - \lambda_T}{k_T/ex_T})$. In general, this approximation will only be a good one if $w_T^f - \lambda_T$ is small relative to (k_T/ex_T)

Estimating Equation 36, we can model the argument of $\Phi(\cdot)$ as a linear function of a constant and the term $(-\nu_t^{ff-}(k_t|\Omega_t^f) + \nu_t^{fh}(k_t|\Omega_t^f))$, which could be computed for any vector of model parameters and the observables. The coefficient on the computed term would identify σ_η, and the estimated constant term would then identify μ_η. In Equation 37, the second probability term could be computed by calculating a critical level of λ_t at which an individual is indifferent between migrating and not migrating and evaluating the conditional cdf of λ_t at this critical level. In the first term, we could model the argument of $\Phi(\cdot)$ as a linear function of a constant and the log of the asset stock, $log\left(\frac{k_t}{ex_t}\right)$. The coefficient on the asset stock term would identify σ_λ, while the constant would identify μ_λ.

A.4 Calculating the Variance of the Parameter Estimates

We use the expansion method outlined in Newey and McFadden (1994), as applied to a Method of Simulated Moments estimator by Gourinchas and Parker (2002), to calculate the standard errors of the parameter estimates in the model. Define $G_{\Pi^M} = E[\frac{\partial g(\mathfrak{p}_i, X_i, \Pi^M, \Pi^w)'}{\partial \Pi^M}]$, which is a $N^g \times N^M$ matrix, where N^g is the number of moment conditions and N^M is the number of variables in Π^M. Similarly, define $G_{\Pi^w} = E[\frac{\partial g(\mathfrak{p}_i, X_i, \Pi^M, \Pi^w)'}{\partial \Pi^w}]$, a $N^g \times N^w$ matrix. Let V_{Π^w} be the covariance matrix for the parameter estimates in the vector Π^w from the first stage wage regressions. Since there are far more observations on labor income in Mexico than on labor income in the United States, and since there is therefore little overlap between the individuals included in the first stage regressions for each distribution, we assume that the parameter estimates for $\overrightarrow{\gamma}^{US}$ and $\overrightarrow{\gamma}^{MEX}$ are uncorrelated, which implies that V_{Π^w} is block diagonal.

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, $g(\mathfrak{p}_i, X_i, \Pi^M, \Pi^w)$. We assume that these observed moment conditions are uncorrelated with the observed moment conditions used to estimate Π^w in the first-stage, an assumption that may be defended on the grounds that the estimation of the parameters in Π^w relies on data that are mostly different from those used to construct the observables, $\mathfrak{p}_i \otimes X_i$.

Then using the Slutsky and central limit theorems, one may show that the term $\sqrt{I}(\Pi^{M*} - \Pi_o^M)$ converges in distribution to a normal random variable with the following asymptotic covariance distribution:

$$V_{\Pi^M} = (G'_{\Pi^M} W G_{\Pi^M})^{-1} G'_{\Pi^M} W[\alpha\Omega_g + AG'_{\Pi^w} V_{\Pi^w} G_{\Pi^M}] W G_{\Pi^M} (G'_{\Pi^M} W G_{\Pi^M})^{-1} \tag{38}$$

Where $\Omega_g = E[g(\mathfrak{p}_i, X_i, \Pi_o^M, \Pi_o^w) g(\mathfrak{p}_i, X_i, \Pi_o^M, \Pi_o^w)']$, $\alpha = \lim_{I\to\infty}(1 + \frac{I}{\rho})$, and A is an $N^w \times N^w$ diagonal matrix with elements of the form $A_{ii} = \lim_{I\to\infty} \frac{I}{J_i}$, with J_i being the number of observations used to estimated the i^{th} parameter in Π^w. Although Equation 38 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.

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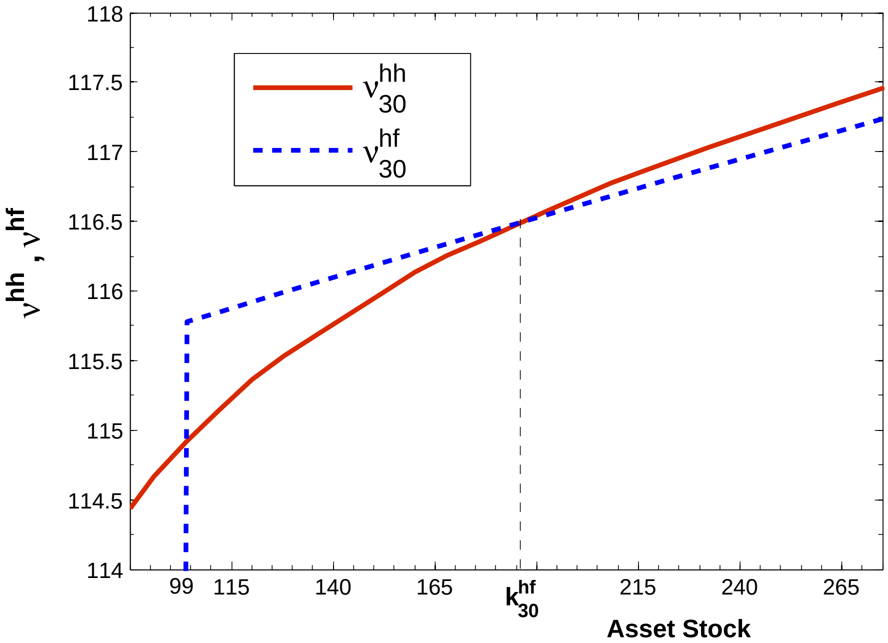
Table 1: Descriptive Statistics: Individual Characteristics

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Education:			**Years in Sample**	9.79	2.66
0-3 Years	0.06	0.24	**Initial Assets:**		
4-6 Years	0.30	0.46	Hectars	0.13	1.84
7-9 Years	0.37	0.48	Properties	0.06	0.25
10-12 Years	0.20	0.40	Businesses	0.02	0.16
13-16 Years	0.07	0.25	**Initial Assets (Dummies):**		
Community Type:			Any Hectars	0.02	0.12
Rancho	0.21	0.41	Any Properties	0.06	0.24
Town	0.27	0.45	Any Businesses	0.02	0.15
Smaller Urban	0.20	0.40	**Initial Family**		
Metro	0.32	0.47	**Migration Experience:**		
Adulthood Cohort:			Father	0.07	0.25
1987	0.18	0.38	Mother	0.01	0.11
1988	0.17	0.37			
1989	0.15	0.36			
1990	0.13	0.34			
1991	0.09	0.29			
1992	0.09	0.29			
1993	0.06	0.24			
1994	0.05	0.22			
1995	0.04	0.19			
1996	0.04	0.19			

N=1165 for all variables. Under Initial Family Migration Experience, the Father and Mother variables are dummy variables indicating whether or not an individual's father and mother had any U.S. migration experience before or during the first year of adulthood.

Figure 1: Value Functions for the Migration and Return Decisions



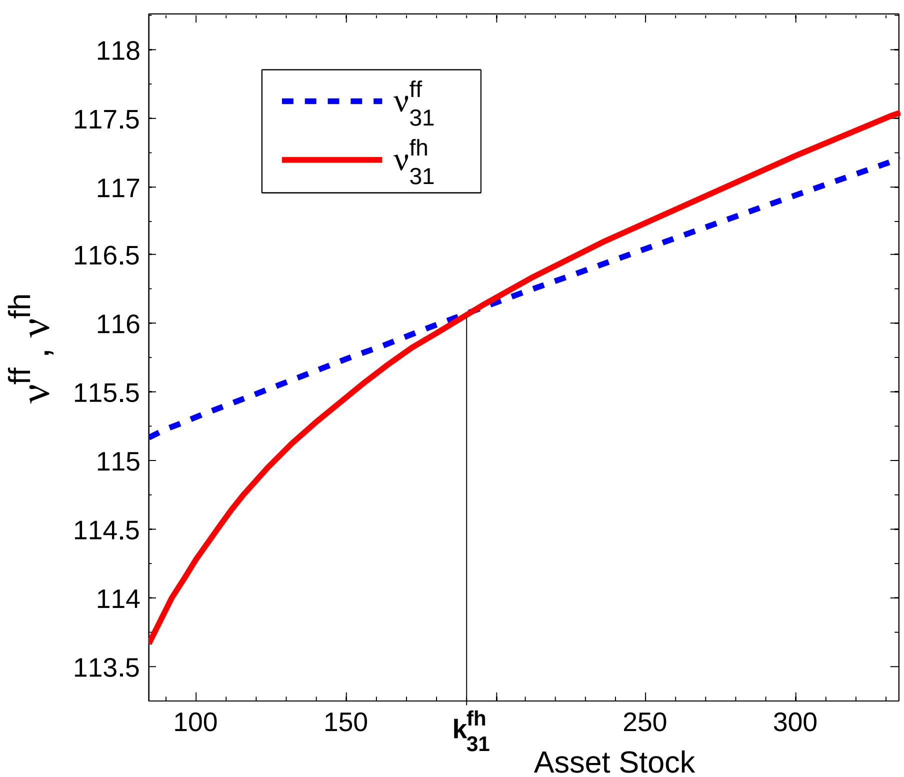
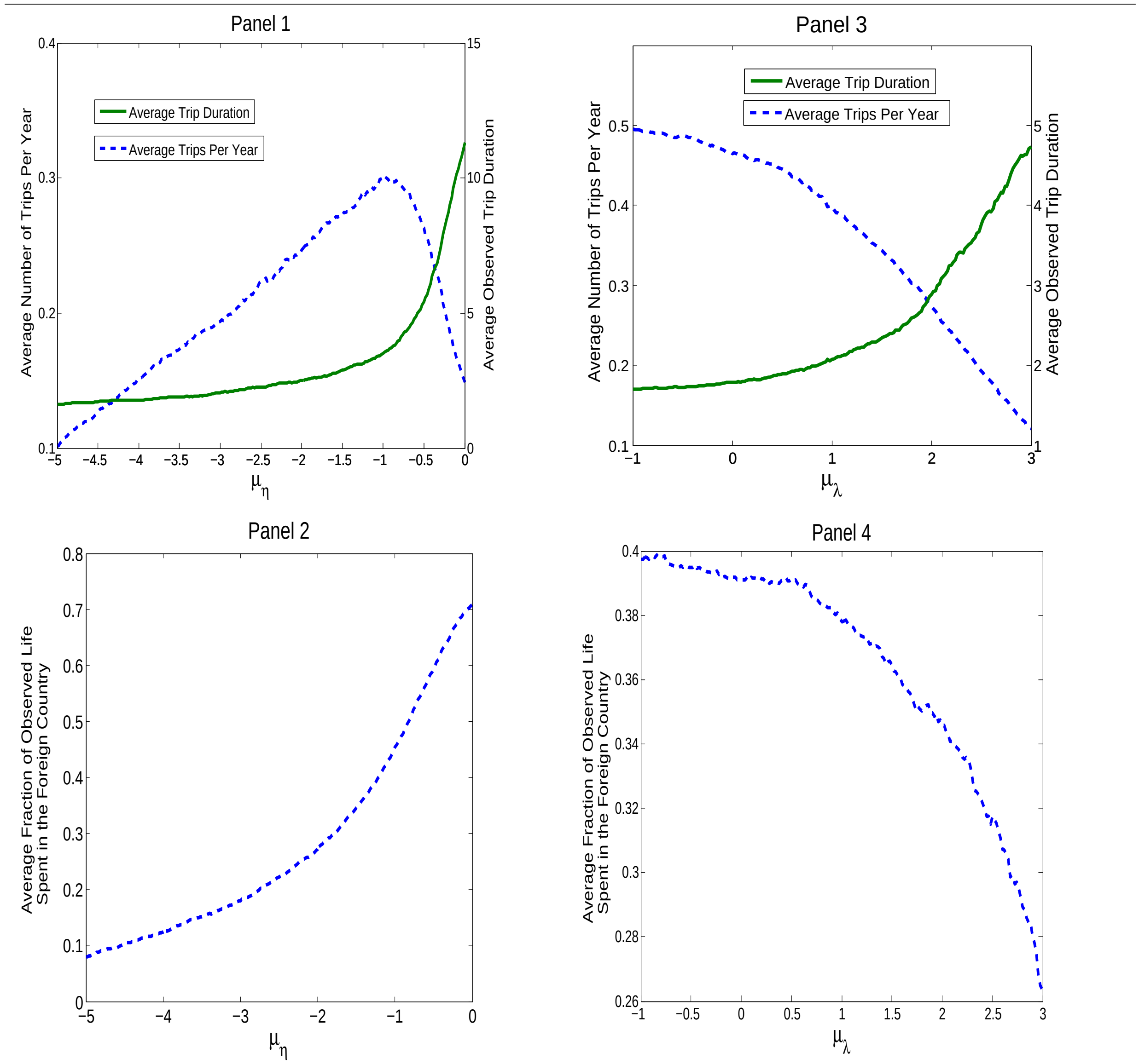


Figure 2: The Effect of μ_η and μ_λ on the Number of Trips and the Duration of Time Spent Abroad in Simulations



For all panels, $\sigma_\eta = .25$, $\mu_h = 2.75$, $\sigma_h = .75$, $\mu_f = 3$, $\sigma_f = .6$, $\mu_e = 2.4$, $\sigma_e = .15$, $\sigma_\lambda = .5$ $\beta = .97$, $ppp = 0.1689$ $R = 1.0109$. For Panels 1 and 2, $\mu_\lambda = 2$. For Panels 3 and 4, $\mu_\eta = -1.5$. Each point on a graph represents averages taken with respect to 500 simulated life histories for an individual with $T = 100$ observed for 20 periods.

Table 2: Descriptive Statistics: Migration Experience

Variable	Complete Sample Mean	Complete Sample St. Dev.	Complete Sample N	Migrants Only Mean	Migrants Only St. Dev.	Migrants Only N
Trips:						
0	0.72	0.45	1165	0	0	324
1	0.20	0.40	1165	0.70	0.46	324
2 or More	0.08	0.28	1165	0.30	0.46	324
Trips (<10 Yrs in Sample):						
0	0.76	0.43	518	0	0	122
1	0.17	0.38	518	0.74	0.44	122
2 or More	0.06	0.24	518	0.26	0.44	122
Trips (≥10 Yrs in Sample):						
0	0.69	0.46	647	0	0	202
1	0.21	0.41	647	0.68	0.47	202
2 or More	0.10	0.30	647	0.32	0.47	202
Pattern Variables:						
m_i^2	0.06	0.24	1165	0.21	0.41	324
m_i^4	0.13	0.33	1165	0.45	0.50	324
m_i^6	0.18	0.39	1085	0.63	0.48	314
m_i^8	0.23	0.42	886	0.74	0.44	273
δ_i	0.08	0.19	1165	0.30	0.26	324
τ_i	0.04	0.09	1165	0.15	0.11	324
$\frac{12\delta_i}{\tau_i}$	-	-		27.56	27.74	324

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 $\frac{12\delta_i}{\tau_i}$ variable measures the average length (in months) of each individual's migratory trips. The Trips variables are dummy variables indicating the associated levels of observed trips.

Table 3: Means of Waiting Time Variables By Education Level and Community Type (Number of Observations in Parentheses)

	m_i^2	m_i^4	m_i^6	m_i^8		m_i^2	m_i^4	m_i^6	m_i^8
Education:					**Community Type:**				
3 Years or Less	0.01	0.10	0.13	0.16	Rancho	0.07	0.18	0.26	0.32
	(70)	(70)	(67)	(63)		(240)	(240)	(229)	(195)
4-6 Years	0.05	0.13	0.19	0.25	Town	0.08	0.14	0.20	0.23
	(350)	(350)	(334)	(283)		(319)	(319)	(297)	(240)
7-9 Years	0.07	0.14	0.20	0.25	Small Urban	0.06	0.16	0.23	0.31
	(434)	(434)	(403)	(325)		(234)	(234)	(219)	(180)
10-12 Years	0.06	0.12	0.17	0.17	Metropolitan	0.03	0.07	0.09	0.11
	(235)	(235)	(218)	(172)		(372)	(372)	(340)	(271)
13-16 Years	0.08	0.09	0.14	0.19					
	(76)	(76)	(63)	(43)					

Note: The number of observations is reported in parentheses below each mean. 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.

Table 4: Means and Standard Deviations of Pattern Variables for Migrants By Education and Community Type

	δ_i	τ_i	$\frac{12\delta_i}{\tau_i}$	N		δ_i	τ_i	$\frac{12\delta_i}{\tau_i}$	N
Education:					**Community Type:**				
3 Years or Less	0.18	0.11	21.53	18	Rancho	0.28	0.16	25.65	95
	(0.23)	(0.04)	(32.26)			(0.24)	(0.13)	(25.20)	
4-6 Years	0.27	0.15	25.11	115	Town	0.34	0.16	30.12	92
	(0.24)	(0.10)	(25.38)			(0.28)	(0.11)	(28.57)	
7-9 Years	0.32	0.16	29.22	126	Small Urban	0.25	0.16	22.86	88
	(0.27)	(0.13)	(28.92)			(0.24)	(0.12)	(26.56)	
10-12 Years	0.37	0.15	31.74	52	Metropolitan	0.34	0.12	34.92	49
	(0.29)	(0.10)	(29.19)			(0.29)	(0.05)	(31.49)	
13-16 Years	0.26	0.15	24.89	13					
	(0.195)	(0.09)	(23.61)						

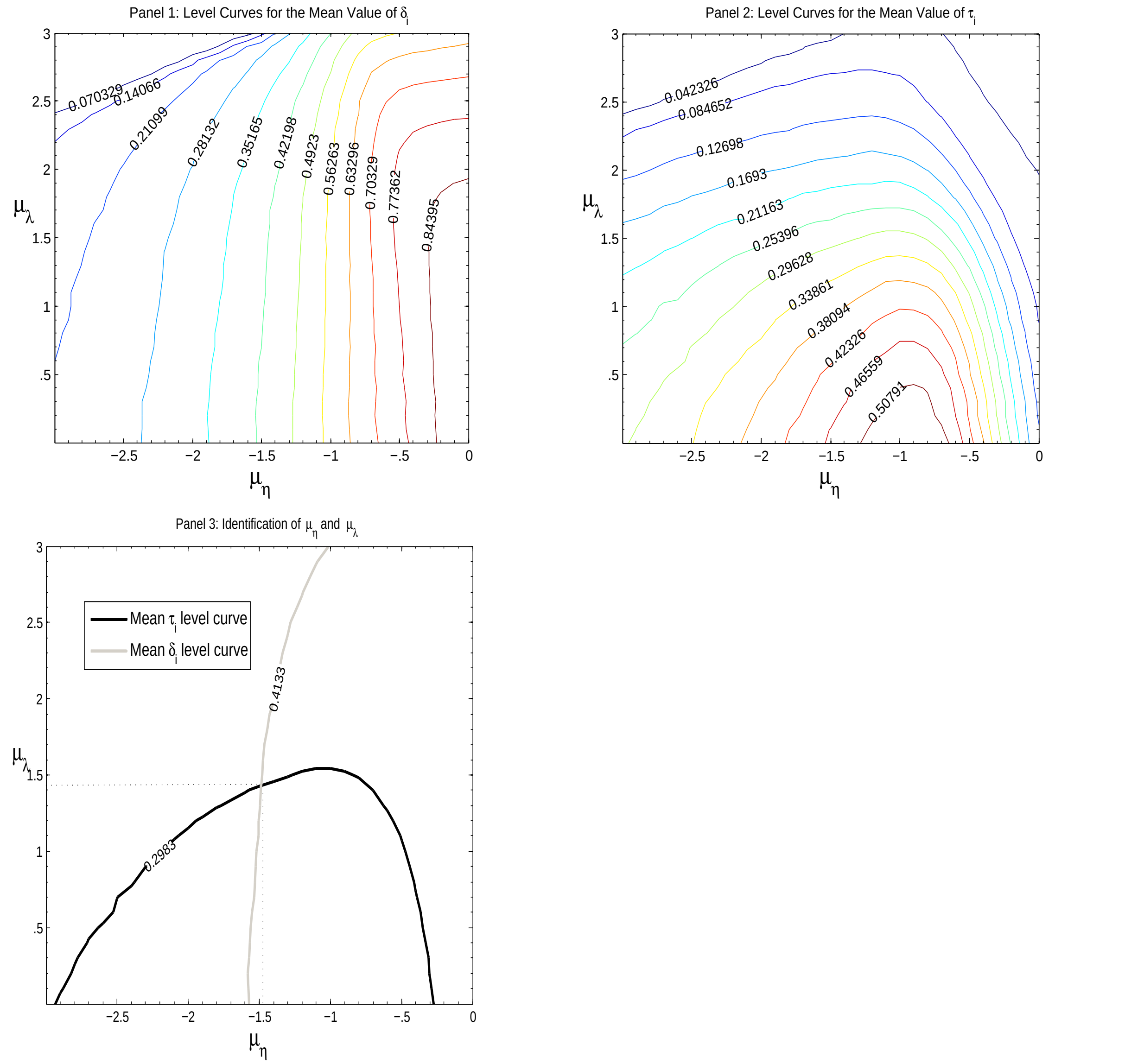
Note: Standard Deviations reported in Parentheses. The δ_i variable measures the fraction of an individual's observed adult life (measured in months) spent in the United States. The τ_i variable measures the number of trips taken by an individual divided by the number of years an individual is observed in the sample. The $\frac{12\delta_i}{\tau_i}$ variable measures the average length (in months) of each individual's migratory trips.

Table 5: Regressions of Migration Pattern Variables

	δ_i		τ_i		$\frac{12\delta_i}{\tau_i}$	
Constant	-0.31***	-0.20**	-0.13***	-0.09**	21.00***	28.18***
	(0.08)	(0.09)	(0.04)	(0.04)	(6.70)	(7.44)
Education: 4-6 Years	0.17**	0.17**	0.08**	0.08**	3.34	2.28
	(0.08)	(0.08)	(0.04)	(0.04)	(7.06)	(7.10)
Education: 7-9 Years	0.18**	0.18**	0.09**	0.09**	6.23	5.80
	(0.08)	(0.08)	(0.04)	(.04)	(7.05)	(7.13)
Education: 10-12 Years	0.14	0.14	0.05	0.06	8.90	9.16
	(0.09)	(0.09)	(0.04)	(0.04)	(7.65)	(7.70)
Education: 13-16 Years	0.04	0.02	0.03	0.02	0.86	-1.22
	(0.11)	(0.11)	(0.05)	(0.05)	(10.20)	(10.26)
Town	-0.10**	-0.10**	-0.06**	-0.06***	3.78	2.69
	(0.05)	(0.05)	(0.02)	(0.02)	(4.08)	(4.25)
Small Urban	-0.04	-0.05	-0.01	-0.02	-3.16	-4.52
	(0.05)	(0.05)	(0.02)	(0.02)	(4.12)	(4.19)
Metropolitan	-0.35***	-0.35***	-0.19***	-0.19***	8.40*	8.11
	(0.06)	(0.06)	(0.03)	(0.03)	(4.96)	(5.02)
Cohort Dummies	No	Yes	No	Yes	No	Yes
N	1165	1165	1165	1165	324	324
Method	Tobit	Tobit	Tobit	Tobit	OLS	OLS

*Note: Stars signify the following: *** significant at the 0.01 level, * significant at the 0.1 level. Standard Errors are reported in parentheses. 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 $\frac{12\delta_i}{\tau_i}$ variable measures the average length (in months) of each individual's migratory trips. The Cohort Dummies control for the year an individual reached adulthood.*

Figure 3: Identification of μ_η and μ_λ



For all panels, $\sigma_\eta = .25$, $\mu_h = 2.75$, $\sigma_h = .75$, $\mu_f = 3$, $\sigma_f = .6$, $\mu_e = 2.4$, $\sigma_e = .15$, $\sigma_\lambda = .5$ $\beta = .97$, $ppp = 0.1689$ $R = 1.0109$. 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 500 simulated life histories for an individual with $T = 100$ observed for 50 periods.

Table 6: US and Mexican Labor Income Regressions

	$log(w^{Mex})$	$log(w^{US})$
Constant	2.00***	1.83***
	(0.12)	(0.16)
Age	0.04***	0.003
	(0.01)	(0.01)
AgeSqr	-0.001***	-0.000
	(0.0001)	(0.000)
Education: 4-6 Years	0.19***	0.10***
	(0.02)	(0.04)
Education: 7-9 Years	0.32***	0.14***
	(0.03)	(0.05)
Education: 10-12 Years	0.53***	0.20***
	(0.03)	(0.06)
Education: 13-16 Years	0.82***	0.27***
	(0.04)	(0.07)
Town	-0.01	0.12***
	(0.03)	(0.04)
Small Urban	0.05*	0.03
	(0.03)	(0.04)
Metropolitan	0.18***	0.004
	(0.03)	(0.05)
Time Trend	-0.03***	0.004
	(0.01)	(0.004)
Crash	-1.19***	
	(0.09)	
TimeTrend*Crash	0.09***	
	(0.01)	
$\widehat{\sigma}$	0.61	0.52
N	4970	1263

*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 an efficient two-step GMM estimator. Labor income is measured in thousands of units of real pesos or dollars. The dependent variable is the log of six times an observed monthly income, since estimation of the structural model proceeds taking six months as the length of a period. Nominal wages are deflated using the Mexican and U.S. CPI series from the September 2007 release of the IMF's International Financial Statistics with 2000 as the base year.*

Figure 4: Border Enforcement and the Real Exchange Rate

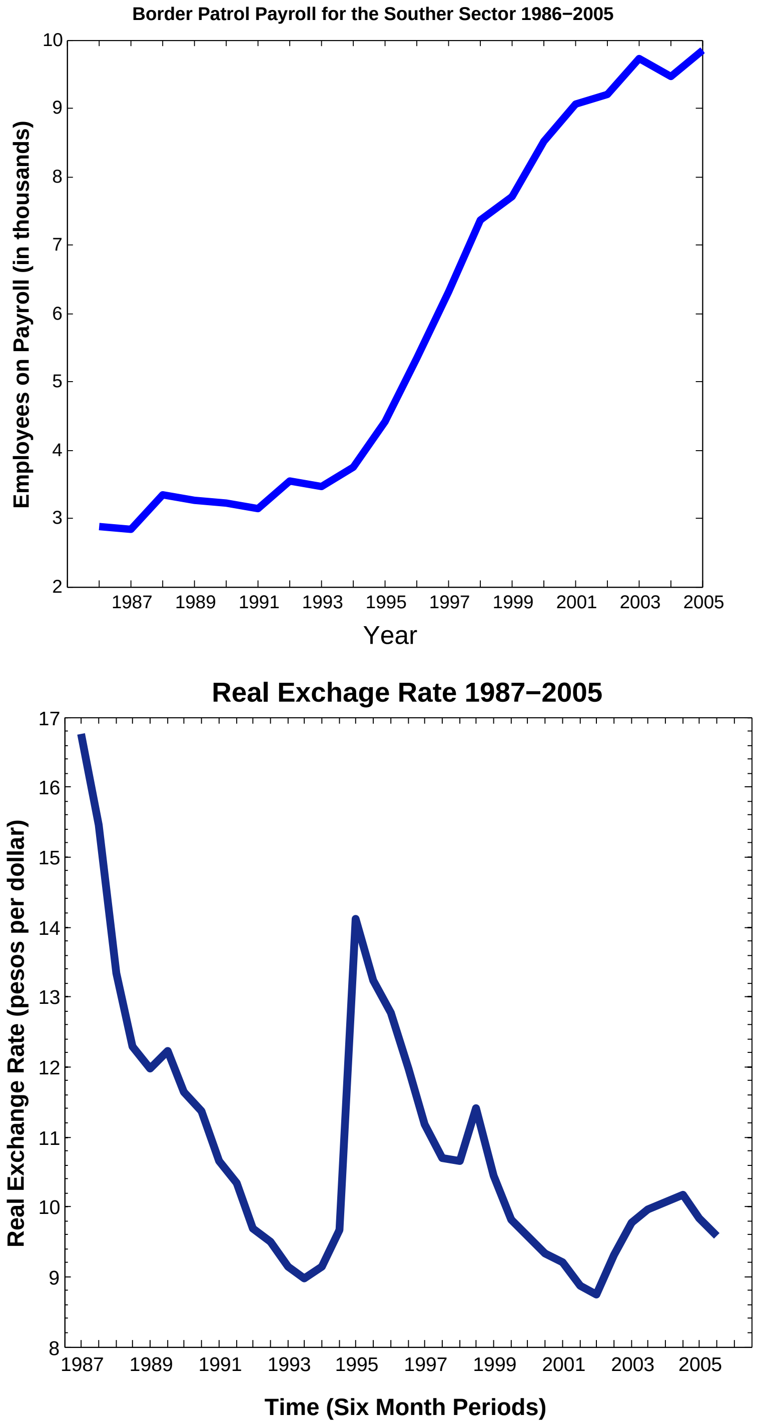


Table 7: Summary of the Empirical Model

Predetermined Constants: R, β, ppp

Wages:

$$\log(w_{i,t}^{US}) = \gamma_{w,0}^{US} + \sum_j \gamma_{e,j}^{US} EDU_{i,j} + \sum_m \gamma_{c,m}^{US} COM_{i,m} + \gamma_T^{US} Trend_t + \varepsilon_{i,t}^{US}$$

$$\log(w_{i,t}^{MEX}) = \gamma_{w,0}^{MEX} + \sum_j \gamma_{e,j}^{MEX} EDU_{i,j} + \sum_m \gamma_{c,m}^{MEX} COM_{i,m} + \gamma_T^{MEX} Trend_t + \gamma_{cr}^{MEX} Crash_t + \gamma_{crT}^{MEX} Trend * Crash_t + \varepsilon_{i,t}^{MEX}$$

Beliefs about ex_t and B_t follow:

$$\log(ex_t) = \gamma_0^{ex} + \gamma_1^{ex} HTrend_t + \gamma_2^{ex} HTrend_t^{-1} + \gamma_3^{ex} Crash_t + \gamma_4^{ex} HTrend_t * Crash_t + \gamma_5^{ex} HTrend^{-1} * Crash_t + \varepsilon_t^{ex}$$

$$\log(B_t) = \gamma_0^B + \gamma_1^B Trend_t + \gamma_2^B Trend_t^2 + \gamma_3^B Crash_t + \gamma_4^B Trend_t * Crash_t + \gamma_5^B Trend_t^2 * Crash_t + \varepsilon_t^B$$

Migration Parameters:

$$\eta_{i,t} = \overline{\gamma}^{\eta} + \sum_j \gamma_{e,j}^{\eta} EDU_{i,j} + \sum_m \gamma_{c,m}^{\eta} COM_{i,m} + \varepsilon_{i,t}^{\eta}$$

$$\lambda_{i,t} = \overline{\gamma}^{\lambda} + \sum_j \gamma_{e,j}^{\lambda} EDU_{i,j} + \sum_m \gamma_{c,m}^{\lambda} COM_{i,m} + \gamma_b^{\lambda} B_t$$

Initial Conditions:

$$k_{i,1} = exp(\overline{\gamma}^k) + \gamma_p^k P_i + \gamma_{fm}^k FM_i$$

$$L_0 = 0$$

Decision Rules:

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

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

Table 8: Structural Estimation Results

	I	II
Location Preference:		
$\overline{\gamma}^{\eta}$	-0.76**	-0.80
	(0.31)	(0.62)
$\gamma^{\eta}_{e,1}$		-0.08
		(0.87)
$\gamma^{\eta}_{e,2}$		-0.01
		(1.04)
$\gamma^{\eta}_{e,3}$		0.05
		(1.20)
$\gamma^{\eta}_{e,4}$		0.12
		(0.69)
$\gamma^{\eta}_{c,1}$		
$\gamma^{\eta}_{c,2}$		
$\gamma^{\eta}_{c,3}$		
γ^{η}_{σ}	0.13	0.22*
	(0.33)	(0.13)
Migration Cost:		
$\overline{\gamma}^{\lambda}$	1.54***	1.57**
	(0.19)	(0.72)
$\gamma^{\lambda}_{e,1}$		-0.12
		(0.43)
$\gamma^{\lambda}_{e,2}$		0.01
		(0.61)
$\gamma^{\lambda}_{e,3}$		0.02
		(0.61)
$\gamma^{\lambda}_{e,4}$		-0.10
		(0.55)
$\gamma^{\lambda}_{c,1}$		
$\gamma^{\lambda}_{c,2}$		
$\gamma^{\lambda}_{c,3}$		
γ^{λ}_{b}	0.56**	0.55*
	(0.23)	(0.33)
Initial Wealth		
$\overline{\gamma}^{k}$	-0.15	-0.39
	(28.03)	(61.30)
γ^{k}_{P}	159.74**	128.66
	(65.12)	(138.18)
γ^{k}_{FM}	78.47**	86.19
	(31.03)	(61.97)

*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 9: Comparison of Empirical and Simulated Moments

	Complete Sample		4-6 Years Edu.		7-9 Years Edu.	
	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated
m_i^2	0.06	0.06	0.05	0.06	0.07	0.06
m_i^4	0.13	0.12	0.13	0.12	0.14	0.13
m_i^6	0.18	0.18	0.20	0.20	0.20	0.19
m_i^8	0.23	0.22	0.27	0.25	0.25	0.23
m_i^{10}	0.26	0.25	0.30	0.29	0.30	0.24
δ_i	0.08	0.10	0.09	0.11	0.09	0.10
τ_i	0.04	0.03	0.05	0.03	0.05	0.03

	10-12 Years Edu.		13-16 Years Edu.	
	Empirical	Simulated	Empirical	Simulated
m_i^2	0.06	0.06	0.08	0.05
m_i^4	0.11	0.11	0.09	0.13
m_i^6	0.17	0.16	0.14	0.22
m_i^8	0.17	0.19	0.19	0.23
m_i^{10}	0.18	0.22	0.26	0.23
δ_i	0.08	0.08	0.04	0.08
τ_i	0.03	0.03	0.03	0.04

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.

Figure 5: Simulated Migration Patterns Under Counterfactual Policy Regimes