Borrowing Constraints, Migrant Selection, and the Dynamics of Return and Repeat Migration

Joseph-Simon Görlach*

September 25, 2019

Abstract

Higher earnings in a migrant's country of origin change migration dynamics: they increase the opportunity cost of migration, but also relax financial constraints. To evaluate the effects on return and repeat migration, I formulate a dynamic model of consumption and location choices. Estimation uses both Mexican and U.S. data sources, and exploits a randomized experiment for identification. I find that an increase in Mexican household earnings shortens migration duration, but raises the average number of migrations. For low-income households, a rise in earnings leads to a more than proportional effect on consumption expenditure in Mexico, arising from repatriated savings.

JEL codes: J15, J61, D15, F22, O15
Keywords: International migration, borrowing constraints

*Department of Economics, Bocconi University, BIDSA, CReAM, IGIER and LEAP; e-mail: josephsimon.goerlach@unibocconi.it. I am grateful for comments by my advisors Christian Dustmann and Jérôme Adda, many colleagues, and numerous participants of seminars and workshops at various institutions.

1 Introduction

Relative to the United States, hourly wages in Mexico have increased by 14.2 percent over the last 20 years. The resulting change in both the affordability and the desirability of migration not only affects the scale and the composition of migrant flows, but also their dynamics: the time immigrants choose to stay in the U.S., as well as their optimal number of migrations. This implies a potential change in the share of immigrants who will settle permanently. While spending time abroad may become less attractive, migrations also become more affordable as earnings increase, in particular for households facing tight credit constraints. As a result, emigration and re-migrations to the U.S. may decrease or increase, depending on which effect dominates. Prohibitive migration costs are an often-cited argument for low emigration rates despite high potential returns.[1] The extent to which financial constraints are binding depends on a potential migrant's assets, earnings, and on the ability to borrow. Hence, policies that increase earnings in migrant sending countries will—apart from raising the opportunity cost of emigration—also help overcome migration constraints. Understanding the channels by which an increase in earnings affects migration decisions is important given the rapid economic development in many low- and middle-income countries, but also for an assessment of various development policies and income support programs.

This paper evaluates the effect of a rise in household earnings in Mexico on emigration, return migration and re-migration when individuals are financially constrained. An analysis of both emigration and return migration requires data and a model that cover agents' choices and outcomes on both sides of the border. To investigate the role of origin country earnings for migration, I thus formulate a dynamic life cycle model of saving and borrowing decisions, and both individual and family location choices, which allows for unobserved heterogeneity in individuals' productivity as well as in their migration preferences. This allows for an evaluation of the effect of earnings changes not only on the response in migration behavior, but also on the composition of the migrant population in terms of observable and unobservable characteristics. Both are important for an assessment of immigration from a host country perspective, and the results in this paper suggest that economic conditions in a migrant's country of *origin* have to be taken into account more strongly also in research about economic outcomes in the *destination*.

One focus of the analysis is on the unobserved monetary cost of migration, the identification of which is inherently related to the extent to which households have access to credit. If households can borrow up to some *unknown* limit to cover part of this cost, it is

[1] See, for instance, McKenzie and Rapoport (2010), Dustmann and Okatenko (2014), Djajić et al. (2016), Bazzi (2017), Majlesi and Narciso (2018), and Mendola (2018).

unclear whether an observed migration has been facilitated by low migration costs or by a generous borrowing limit. Comparable studies estimating migration costs thus assume that individuals have no access to credit. While this assumption may be a plausible simplification for many at the bottom of the income distribution, it is violated for a considerable part of the Mexican population, as I document in this paper.

A household's access to credit likely depends on its income, as suggested by the strong positive correlation between labor income and household debt found in the data. To achieve identification of this income dependence of credit access despite a potential correlation of individual productivity with the preference for migration (and thus the demand for credit), I use experimental variation in income from the randomized introduction of the Mexican cash transfer program Progresa. While this exogenous income shifter affects both borrowing and the probability to emigrate, the randomized cash transfers from the program provide income variation that is credibly uncorrelated with unobserved innate preferences. The treatment effect of the program on household borrowing is used as an additional moment in the structural estimation of the model, which together with migrations observed along the wealth distribution allows a joint identification of migration costs and debt limits. Note that randomized variation from the program cannot be used to identify the effect of income on migration duration and repeat migration, as the survey did not follow individuals across the border. Rather, the analysis of migration dynamics requires a more structural approach that models choices in the destination country in conjunction with outcomes in the country of origin, and an econometric framework that can utilize data from both sides of the border. Nonetheless, the experimental variation can be used for identification of additional parameters in a model that is more flexible in terms of unobserved heterogeneity and access to credit.

I estimate the model using data from the Mexican Family Life Survey, the U.S. Survey of Income and Program Participation, the Mexican Migration Project and Progresa's evaluation survey. I explicitly address the non-representativeness of some of these surveys via a flexible and novel estimation of unobserved heterogeneity types. In particular, I account for a potentially different composition of the non-representative samples with respect to unobserved productivity and individuals' preference for migration. I then use the model to evaluate the dynamic effect of higher earnings in Mexico on both compositional changes of the immigrant population due to selective emigration and return migration, as well as the behavioral changes in the length of stay and the frequency of migrations.

Contrary to a model without financial constraints, in which an increase in origin earnings would unambiguously decrease the tendency to migrate, I find that a rise in earnings in Mexico raises emigration and increases the number of trips per migrant. The effect on emigration is inverted U-shaped along the wealth distribution and in line with reduced form evidence. Reduced form analysis, however, only identifies this net effect of an increase in the opportunity cost of migration and a relaxation of financial constraints. Using information on both observed saving and location choices within the structural estimation of the model instead allows me to identify preference parameters and financial constraints, and hence to distinguish these two channels. This is important for various policies. For instance, better credit access in developing countries will have a similar effect as a rise in income only if financial constraints are a major impediment to migration. On the other hand, policies that raise immigrant earnings at the destination only will mitigate the effect of a rise in earnings at the origin if financial constraints are negligible. The empirical framework utilizes data from both sides of the border, with the model accounting for selection into either location. This facilitates an analysis also of migration duration and repeat migration.

I find that conditional on ever migrating, a 10 percent increase in Mexican earnings raises the average number of trips by 5.8 percent. The average time spent in the U.S. per trip is shortened by 10.3 percent. These results are driven by behavioral adjustments rather than by compositional changes within the migrant population. I further use the model to evaluate the effect on aggregate consumption expenditure in Mexico. For poor individuals, higher earnings lead to a more than proportional increase in domestic consumption due to repatriated savings of temporary migrants. I show that accounting for credit access is empirically important, and that a model without borrowing underestimates the cost of migration by up to 65 percent.

My work contributes to a relatively young literature that uses dynamic life cycle models to analyze various aspects of temporary international migration. Papers by Colussi (2003), Thom (2010), and Lessem (2018) focus on the effect of border enforcement on Mexico-U.S. migration. Bellemare (2007) and Rendon and Cuecuecha (2010), instead, investigate job search and outmigration behavior of immigrants in Germany and the U.S., whereas Kırdar (2012) and Nakajima (2015) evaluate the social insurance and fiscal contributions of temporary migrants. Beside the difference in the questions examined, the distinguishing features of the model I use relative to those presented earlier include that I account for borrowing, that asset accumulation and family migration are modeled jointly, that I include experimental variation in the estimation, which allows a richer specification in terms of unobserved heterogeneity, and that I explicitly account for seasonal variation in labor demand.[2] While the focus of Lessem (2018) is on the impact of border enforcement on migrations in a family

[2]See also Dustmann and Görlach (2016) for a survey of this literature. In addition, structural models have been used to analyze *internal* location choices (see e.g. Gemici, 2011; Kennan and Walker, 2011; Bryan et al., 2014; Buchinsky et al., 2014; Kleemans, 2015; Girsberger, 2017; Piyapromdee, 2017; Llull and Miller, 2018; Morten, 2019; Bryan and Morten, forthcoming; Oswald, forthcoming).

context, hers is the only paper that also evaluates the importance of home country wages on migration decisions. In contrast to her analysis, my paper investigates migration dynamics under financial constraints in the presence of unobserved heterogeneity in preferences and productivity, where exploiting experimental variation in income allows a flexible specification of access to credit to finance a costly migration. My findings show that some of the effects of a rise in Mexican earnings may reverse when accounting for financial constraints.

My paper also complements reduced form studies that estimate the effect of an income shock on the probability to emigrate. In the context of Mexico-U.S. migration, Angelucci (2015) uses exogenous variation in incomes from Progresa cash transfers to evaluate the net effect on emigration rates.[3] My paper builds on this work by disentangling the rise in the opportunity cost of migrating to the U.S. and the relaxation of financial constraints. It further provides estimates of the more dynamic effects on return and re-migration choices that result from the income shock.

By introducing exogenous variation of the type used in the reduced form literature to the analysis of migration dynamics based on structurally estimated life cycle models, this paper also contributes to the growing literature that combines structural estimation with experimental variation. While some studies use policy reforms or randomized treatments of sub-populations to examine the external validity of structural models estimated on the non-treated sample (e.g. Lise et al., 2004; Todd and Wolpin, 2006), exogenous variation can also be used for identification of model parameters that are not well identified using observational survey covariations alone (as in e.g. Attanasio et al., 2012; Gole and Quinn, 2016; DellaVigna et al., 2017). This is the approach taken here, where identification of the income dependence of debt limits requires information on borrowing in response to exogenous variation in incomes that can be plausibly separated from heterogeneous preferences for migration. The randomized experiment is thus used to allow for a more flexible specification of the structural model regarding access to credit and unobserved heterogeneity. The structural model in turn allows evaluating the longer term effects of the randomized treatment, in particular toward a more dynamic analysis of return and repeat migration, and a disentangling of the different channels that connect earnings changes to migration.

The remainder of the paper is organized as follows. Section 2 describes the data sources used. Section 3 presents the model on which my results are based, whereas Section 4 dis-

[3]In other contexts, Imbert and Papp (2015) use cross-state variation in a public works program in India, where they find a negative effect of participation in the program on urban migration. For international migration from Indonesia, Bazzi (2017) uses rainfall and commodity price shocks to evaluate determinants of emigration. In line with the existence of credit constraints, he finds a positive effect of income shocks on emigration from villages with relatively more small landholders. See Clemens (2014) for a broader survey of this literature.

cusses identification and addresses issues arising in the combination of multiple, partly non-representative, data sources. In Section 5, estimation results are reported and the dynamic implications of higher earnings in the country of origin are evaluated.

2 Data and Descriptives

An analysis of Mexican emigration and return migration that accounts both for heterogeneity in migration preferences and for heterogeneity in productivity on both sides of the border requires information on individuals' choices and outcomes in Mexico, as well as for both temporary and permanent migrants in the U.S. In addition, credible identification of income dependent credit access requires experimental variation in income that can be separated from the unobserved preference for a costly migration. The estimation thus relies on multiple micro data sets: the Mexican Family Life Survey, the U.S. Survey of Income and Program Participation, the Mexican Migration Project and the Progresa evaluation sample. Section 4.2 details a novel procedure to account for the non-representativeness of some these samples.

Mexican Migration Project (MMP). Given the lack of data sets that track migrants across international borders, analyses of repeat migration rely almost exclusively on retrospective migration histories from the MMP. The MMP's complete retrospective life histories contain detailed information on employment, family status and migrations for each household head and spouse. To illustrate the prevalence of repeat migration, Figure 1a displays the distribution of the number of trips made by Mexican men who have reached age 65 or older, and are thus likely to have completed their total lifetime number of labor migrations. In this sample of former U.S. migrants, more than 60 percent report having been to the U.S. more than once, among whom about two thirds have migrated more than twice. Figure 1b shows the distribution of duration of the most recent migration. Although there is much variation in migration duration, a considerable proportion, about one third, has returned within one year after emigration.[4] As the MMP only captures uncensored migration spells and does not cover permanent emigrants, I also use data from the U.S. Survey of Income and Program Participation detailed below.

For the main analysis, I restrict the sample to the years 1996-2007,[5] and exclude in-

[4]That temporary migration is not a recent phenomenon has been documented by Bandiera et al. (2013).

[5]The reason for this is threefold: (1) a series of policy changes since the Immigration and Control Act (IRCA) of 1986 gradually tightened control of the U.S. southern border, culminating in the Illegal Immigration Reform and Immigrant Responsibility Act of 1996. Each of these reforms, which include some more local measures, such as Operation Hold-the-Line in 1993 and Operation Gatekeeper in 1994, expanded border control (see e.g. Gathmann, 2008, for details). (2) a major tightening of the border started with the construction of fences along extended parts of the border in 2007, following the Secure Fence Act signed in late 2006 (Public Law 109-367-Oct. 26, 2006). Starting in 2008, the U.S. Border Patrol further rolled out the

dividuals who were born in the U.S. Lastly, I restrict attention to male household heads aged 16-64 without tertiary education. I do, however, use information on migrations of their spouses to identify model parameters relating to dependent family members' residence location. The same restrictions apply to the other data sets discussed below. The focus on individuals without college education yields a more homogeneous population to which the model of Section 3 is applied, and allows me to exclude for instance student migration.[6] The MMP is representative only within the communities surveyed, whereas these communities are a non-random selection within Mexico. The MMP has been criticized for its bias toward communities with a strong migration history, including by studies investigating migrant selection (see e.g. Orrenius and Zavodny, 2005; Hanson, 2006; McKenzie and Rapoport, 2007; Fernández-Huertas Moraga, 2011). I explicitly address this non-randomness in the estimation as explained in Section 4.2, also utilizing representative data sources.

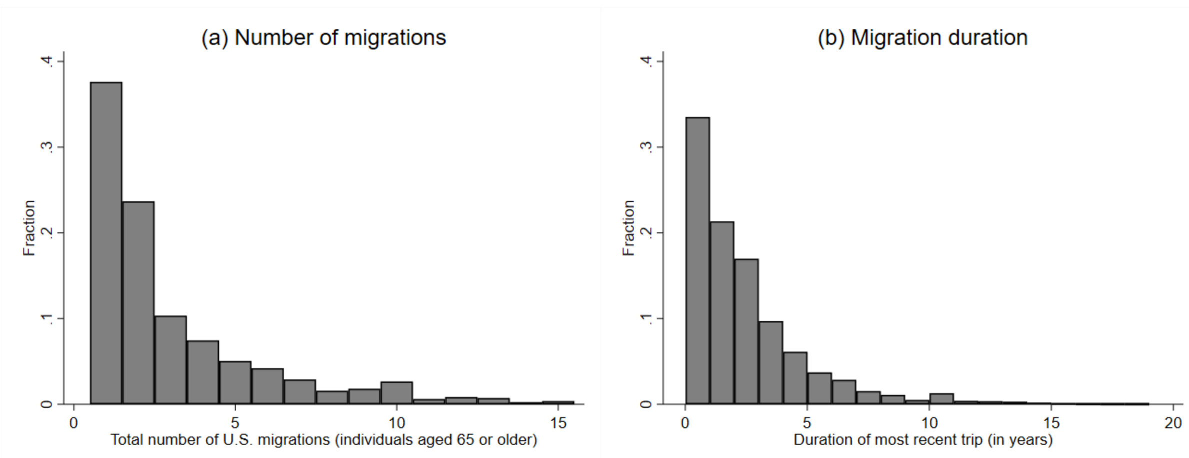


Figure 1: Number of migrations and migration durations. Source: MMP 143. Figure 1a shows the distribution of the number of migrations made per returned migrant by age 65. The distribution is based on the MMP cross-sectional files, restricting the sample to Mexican-born non-tertiary educated males aged 65 or older at the time of the survey. Figure 1b, showing the distribution of migration duration, refers to the last trip to the U.S. by Mexican-born non-tertiary educated males aged 16-64 at the time of the survey.

Mexican Family Life Survey (MxFLS). As a nationally representative data set, I use the 2002 and 2005-06 waves of the MxFLS.[7] In addition to longitudinal information, including on earnings, the MxFLS reports whether and for how long individuals have been

so-called Consequence Delivery System, which involved an increase in administrative and criminal sanctions against undocumented migrants (Bazzi et al., 2018). (3) the focus on post-1996 data avoids contamination of my results by the peso crisis of December 1994 and the most abrupt economic woes that followed. For an investigation of migration patterns across business cycles, see Lessem and Nakajima (2019).

[6]In the MMP data, and given the other restrictions, less than 8 percent of individuals are tertiary educated; in the nationally representative Mexican Family Life Survey, this applies to less than 11 percent.

[7]To stay within the same sample period, I do not use later MxFLS waves.

to the U.S. This is used to identify the distribution of preferences for migration.[8]

In the presence of positive migration costs, imperfect credit markets have been highlighted as an important constraint to international migration (Chiquiar and Hanson, 2005; McKenzie and Rapoport, 2010; Dustmann and Okatenko, 2014; Djajić et al., 2016; Bazzi, 2017; Mendola, 2018). Motivated by this, borrowing has been ruled out in existing dynamic models of international migration that account for asset accumulation (Rendon and Cuecuecha, 2010; Thom, 2010). While this may be plausible for individuals at the low end of the earnings distribution, about one fifth of the households in my sample reports holding negative net assets. Debt limits for these individuals thus must be at non-zero levels, and possibly for others, who do not *choose* to borrow, too.[9] For the non-tertiary educated in-

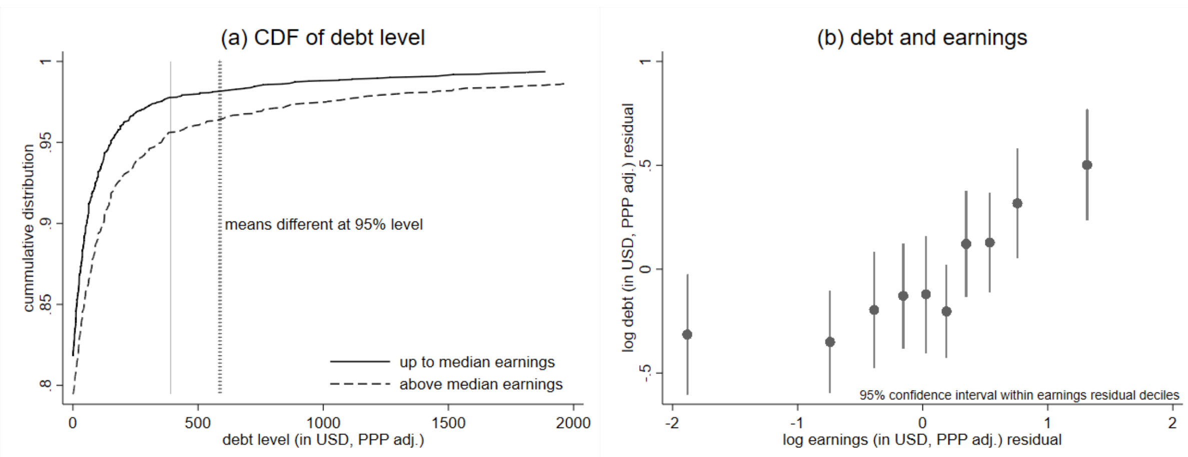


Figure 2: Distribution of debt levels by earnings. Source: Mexican Family Life Survey, 2002, 2005. Debt is calculated as negative net assets (in PPP adjusted USD). The figure shows (a) the cumulative distribution of debt, with mean (positive) debt levels, and (b) mean log debt residuals against earnings residual deciles, each net of age, education, family status and year of observation. The sample includes non-tertiary educated male household heads aged 16-64.

dividuals in my sample, Figure 2 suggests a positive relation between debt and earnings. Panel (a) shows the cumulative distribution of debt, separately for households with above and below median earnings. At the mean, the difference in debt levels between these groups is significant at the 95 percent level, with high earning households on average holding about 50 percent more debt than households with earnings below the median. The same positive relation conditional on age, education, family status and year of observation is depicted in panel (b), which plots mean residuals of (log) debt against deciles of (log) earnings residuals.

[8]A comparison of the MxFLS to the larger Encuista Nacional de la Dinámica Demográfica yields reassuringly similar propensities to migrate: the fraction of non-tertiary educated men aged 16-64 who report having returned from the U.S. during the past five years is 1.77 percent in the ENADID 2006, while it is 1.62 percent in the MxFLS sample.

[9]See also Friebel and Guriev (2006) for a theoretical analysis of debt-financed migration.

Survey of Income and Program Participation (SIPP). As long-term emigrants are not well represented in Mexican surveys, I further use data from the U.S. SIPP, a panel survey with a large enough sample size to allow a separate analysis of Mexican immigrants. A large share of Mexican migrants work in agriculture, construction and gastronomy, and thus in seasonally volatile sectors. The SIPP provides monthly information suitable to assess the importance of seasonality. Figure 3a shows that seasonality in employment rates is indeed prevalent. Seasonal variation in labor demand is in fact likely stronger, as migration and thus labor supply are pro-cyclical. This is supported by U.S. Border Patrol data on monthly apprehensions, which suggest an about twice as high number of apprehensions at the U.S. southern border during the summer months than in winter (Figure 3b). To account for this feature of Mexico-U.S. migration, the model in Section 3 allows job offer and loss probabilities to vary by season.[10] In line with my restriction of the MMP sample, I use the three SIPP panels 1996-2001, 2001-2004 and 2004-2007.

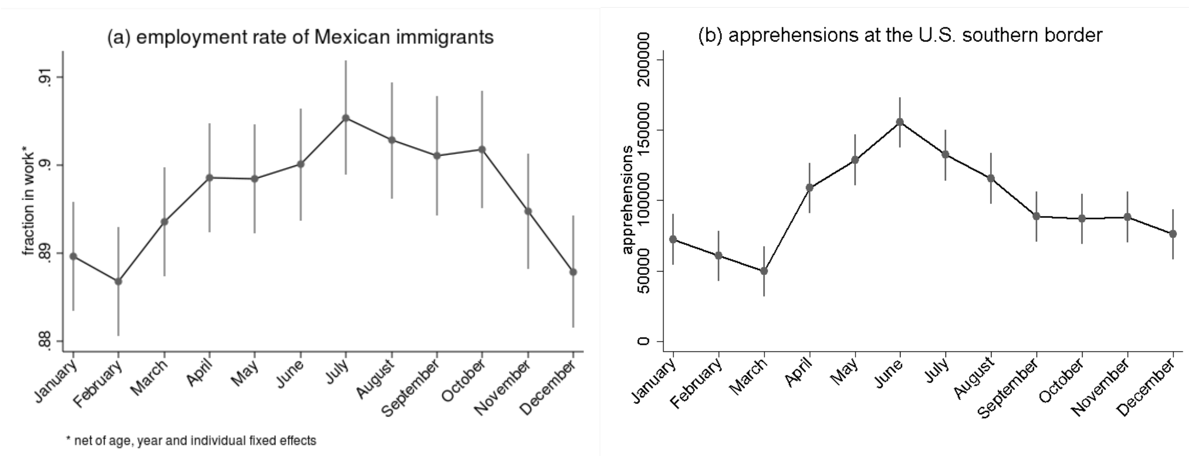


Figure 3: Seasonality. Sources: (a) SIPP, 1996-2007; (b) U.S. Border Patrol, 1999-2007. The graphs show seasonality in (a) the share among non-tertiary educated Mexican-born male household heads aged 16-64 residing in the U.S. who worked for at least one week during the respective month, and (b) average monthly apprehensions at the U.S. southern border. Vertical lines show the 95% confidence intervals.

The main variables used from each of these three data sources are listed in Table 1. Panel (a) separately displays means and standard deviations in different reference populations within the MMP: for the life history files and for an individual's most recent migration. The top most panel further distinguishes between moments of the full pooled sample, and of (retrospective) observation points in the U.S. The first entry shows the strong tendency to

[10]Dynamic models of international migration have so far abstracted from seasonality in labor demand, which has received more attention in analyses of internal migration (see e.g. Bryan et al., 2014; Imbert and Papp, 2015, forthcoming; Meghir et al., 2015; Morten, 2019; Munshi and Rosenzweig, 2016; Rosenzweig and Udry, 2019).

migrate from communities sampled by the MMP, with 5.2 percent of individuals spending at least part of any year in the U.S.

Panels (b) and (c) respectively list variables used from the MxFLS and the SIPP. As shown in Figure 2a, close to one fifth of the Mexican population report having negative net assets, with debt levels averaging around 500 USD (all monetary variables are PPP adjusted). Immigrants surveyed by the SIPP have been to the U.S. on average for 16.7 years. This is considerably more than the average migration duration of 4.2 years for the exclusively temporary migrants covered by the MMP, and highlights the importance of using a data source that includes permanent migrants as well.[11] To examine whether the long mean migration duration observed in the SIPP merely reflects an over-representation of permanent migrants, I contrast this to the same magnitude reported in U.S. Census and American Community Survey data. These data provide information on migration duration for large repeated cross-sectional samples of immigrants in the United States and may be less prone to non-response than the SIPP. Applying the same sample restrictions as for the SIPP, the mean number of years immigrants have spent in the U.S. is 17.8 in Census and ACS data covering the period 2000-2007, and thus reassuringly similar to the number computed for the SIPP sample. Finally, average earnings of Mexicans in the U.S. are about 1.5 log points higher than average earnings in Mexico, suggesting a strong incentive to migrate for many individuals and/or a positive selection of migrants.

Progresa evaluation data. The positive correlation between earnings and debt shown in Figure 2 can result either from better credit *access* for individuals with higher earnings, or from a stronger preference for migration of the same individuals, and thus a higher *demand* for credit. To identify the income dependence of credit access despite a correlation of unobserved productivity with preferences for the U.S., I use evaluation data from Progresa, an initially randomized conditional cash transfer program in Mexico. In particular, I use information on differential loan take-up in treatment and control communities, which can be attributed to the randomized variation in income. This experimental income variation is orthogonal to unobserved innate preferences. Conditional on those preferences, Section 3 models the demand for credit explicitly. In the model used, location preferences and other parameters determining credit demand (e.g. risk aversion) are identified from observed savings and location choices in the other data sets. Given this demand side, the program's randomized income variation then identifies agents' access to credit.[12]

Similar to the MMP, households eligible for Progresa are not representative of the Mexi-

[11]Note, however, that the average migration duration observed in the SIPP is conditional on migrants not having left prior to the survey. Return migration is modeled explicitly in Section 3 to account for this.

[12]This requires that the credit constraint is binding for at least some individuals, which the simulations in Section 5 show indeed is the case

Table 1: Summary statistics for the three main data sources used.

(a) Mexican Migration Project (MMP)

Life history files

Full pooled sample			When in the U.S.		
Variable	Mean	Std. dev.	Variable	Mean	Std. dev.
Is in the U.S.	0.052	0.221	Legal status	0.273	0.446
Number of trips*	2.237	2.593	Working	0.892	0.310
Total U.S. experience (in years)*	4.191	4.497	Family in the U.S.	0.111	0.314
Individuals	10,202			1,366	

Cross-sectional files, information about last U.S. migration

Variable	Mean	Standard deviation
Migration duration (in years)	1.923	1.687
Total amount saved or remitted (in USD)	8,782.536	7,186.547
Individuals	1,291	

(b) Mexican Family Life Survey (MxFLS)

Variable	Mean	Standard deviation
Been to the U.S.	0.126	0.332
Been to the U.S. with family*	0.488	0.500
Last migration duration (in years)	2.457	3.991
Age	42.276	11.474
Has dependent family	0.941	0.235
Working, Oct-Mar	0.907	0.290
Working, Apr-Sept	0.885	0.319
Log annual earnings (in USD, PPP adj.)	8.246	0.955
Net assets (in USD, PPP adj.)	1,067.702	14,209.370
Has debt	0.187	0.390
Amount of debt (in USD, PPP adj.)	502.828	1,773.736
Individuals	5,810	

(c) Survey of Income and Program Participation (SIPP)

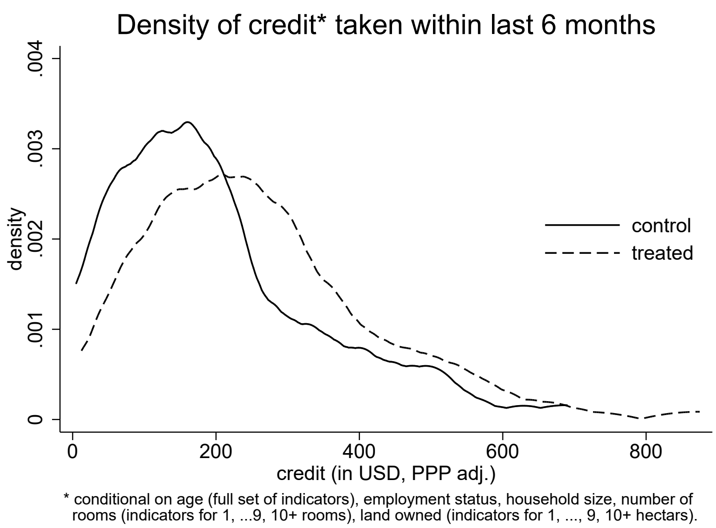
Variable	Mean	Standard deviation
Years since immigration	16.678	9.789
Age	38.626	10.231
Working, Oct-Mar	0.887	0.294
Working, Apr-Sept	0.901	0.272
Log annual earnings (in USD)	9.792	0.755
Individuals	1,754	

Note.— MMP, 1996-2007; MxFLS, 2002, 2005; SIPP, 1996-2007. In each case, the sample includes non-tertiary educated Mexican-born male household heads aged 16-64. SIPP statistics on age, years since immigration and earnings are based on the March survey. Individuals are considered working in a given half-year if this is the case in at least 4 months. Monetary values are deflated to 2005, and adjusted by purchasing power parities if referring to Mexico.
* Conditional on ever having been to the U.S.

can population, which is accounted for in the estimation as explained in Section 4.2. Starting in 1998, eligible families in program communities received cash transfers, conditional on their children's school attendance. Judging from school attendance in control communities, the transfer was in fact unconditional for low-income families with children up to the age of 14, of whom over 97 percent attended school even in the absence of the program. For the estimation, I thus restrict the sample to these families. Further detail on Progresa is provided in Appendix A.

The data reveal that loans taken out by eligible families in program localities during the 6 months leading up to November 1998, when evaluation data were collected, are considerably higher than in control localities. Figure 4 depicts the conditional density of these recent loans in the two groups of locations.[13] In Section 4.1, I provide an estimate of the average of this treatment effect. This non-parametrically identified effect serves as an additional moment in the structural estimation, and allows identification of a more flexible specification of households' access to credit in the model presented in the next section.

Figure 4: Progresa's monthly cash transfers and new loan take-up.



Sources: Progresa, November 1998. The figure shows the distribution of log amounts of loans taken within the previous 6 months by treatment status. The sample includes male heads aged 16-64 of eligible households with children aged 8-14 attending school. The density is computed using an Epanechnikov kernel with 3/4 of the optimal bandwidth to prevent oversmoothing.

[13]Borrowing is net of a full set of age indicators for the male household head, his employment and marital status, as well as the number of household members. To proxy for pre-program wealth, I further include indicators for the number of rooms and the amount of land owned by the household. Appendix A shows the balancing of these variables.

3 Model

The model is chosen to reflect emigration, return migration and re-migration behavior in conjunction with asset accumulation and loan take-up under financial constraints, and accounting for unobserved heterogeneity in preferences and productivity. The aim is to provide a framework within which the effect of origin country earnings on migration dynamics can be evaluated, and different mechanisms can be disentangled. The model accounts for monetary migration costs, as well as for the possibility that part of this cost can be covered by loans. This section describes the primitives of the model, including agents' information set and choices, state variable transitions and the timing of choices, and finally the dynamic specification of the model. Additional details can be found in Appendix B.

State variables. A household head i at time t makes decisions based on age a_{it}, employment status $e_{it} \in \{w, nw\}$, on whether there are dependent family members $f_{it} \in \{0, 1\}$, current household head and family location $\mathbf{l}_{it} \equiv \left(l_{it}, l_{it}^{f}\right) \in \{MX, US\}^2$, legal status in the U.S. $d_{it} \in \{0, 1\}$, total U.S. experience X_{it}^{US}, the accumulated stock of assets A_{it}, and current season $s_t \in \{summer, winter\}$. Furthermore, decisions are based on information unobserved by the econometrician. This includes an individual's productivity in different locations, $\alpha_i \equiv \left(\alpha_i^{MX}, \alpha_i^{US}\right)$, preferences π_i^{US} towards the destination country, and transitory shocks to earnings and locational preference, v_{it}^{l} and $\varepsilon_{it}^{\mathbf{l}}$. The vector $\Omega_{it} \equiv (a_{it}, e_{it}, f_{it}, \mathbf{l}_{it}, d_{it}, X_{it}^{US}, A_{it}, s_t, \alpha_i, \pi_i^{US}, v_{it}^{l}, \varepsilon_{it}^{\mathbf{l}})$ collects the state variables observed by an agent at time t, though some of this information is revealed sequentially within the period, as will be detailed below. In the estimation, a period corresponds to six months.

Family, legal status and location. At the beginning of each period, agents gain or lose dependent family with age dependent transition rates $p_{f+}(age_{it})$ and $p_{f-}(age_{it})$.[14] Also at the beginning of the period, individuals learn whether they have a legal permit to live and work in the U.S. Transitions rates $p_{d+}(age_{it}, e_{it})$ and $p_{d-}(age_{it}, e_{it})$ for an individual's legal status vary with age and employment status. The timing in the model is such that after family and legal status are known, household members choose a location. Besides the financial constraint to migration detailed below, undocumented migrants face the risk of apprehension at the border, so that attempted migrations fail with probability p_a. When there is dependent family, either no one, all, or just the household head may migrate. In data from the Mexican Migration Project, the probability of a female spouse migrating while the male household head stays in Mexico is only 6 percent of the reverse. I thus exclude this option. To further save on computation time, I assume that all family members share

[14] These are piecewise linear functions constrained by a standard normal cdf to yield probabilities between 0 and 1. See Appendix B, also for other functions introduced in this section.

the same legal status in the United States. For married migrants sampled by the MMP this is true in 96 percent of cases. Finally, it is assumed that when there is dependent family, families make consumption and location decisions in agreement, so that choices maximize household welfare. Individuals choosing to migrate face a monetary cost, which varies by age and whether an immigrant holds a U.S. visa, as well as by whether a household member has previously been to the U.S.

Employment and earnings. Job offers arrive at a rate $\lambda_w(\Omega_{it})$, and jobs are lost at a rate $\lambda_{nw}(\Omega_{it})$, each depending on individual characteristics such as age and time spent in the U.S., but also on seasonally varying aggregate labor demand. Both functions are location specific, and in the U.S. also depend on a worker's legal status. I focus on the extensive margin of employment and assume that individuals either work full time or do not work. If working, log biannual earnings in location $l \in \{MX, US\}$ are given by

$$\log y(\Omega_{it}) = \alpha_i^l + f^l(a_{it}, X_{it}^{US}) + v_{it}^l,$$

where unobserved productivity α_i^{MX} in Mexico and α_i^{US} in the U.S. can be arbitrarily distributed and may be correlated with the unobserved preference π_i^{US} for being in the U.S. (see the specification of preferences below). The function $f^l(\cdot)$ is a flexible location-specific spline function of age and the U.S. experience an individual has accumulated up to time t. Idiosyncratic shocks to log earnings, v_{it}^l, are assumed to be independent and normally distributed across time and individuals, with mean zero and location specific variance $\sigma_{v^l}^2$. Individuals retire at age a^{ret} and from then until the end of life receive retirement benefits $y^{ret}(\Omega_{it})$.

Budget constraint. The main motive for temporary migration in the model is financial wealth accumulation for an increase in future consumption and the buffering of labor market shocks. I assume a standard intertemporal budget constraint augmented by migration cost $C(\Omega_{it})$ to relate current assets A_{it} to assets A_{it-1} carried over from the previous period, current earnings $y(\Omega_{it})$ and consumption c_{it},

$$\begin{aligned} A_{it} \leq (1+r)A_{it-1} + y(\Omega_{it}) - c_{it} \quad &- \quad \mathbb{1}[l_{it-1} = MX \cap l_{it} = US]C(\Omega_{it}) \\ &- \quad \mathbb{1}[l_{it-1}^f = MX \cap l_{it}^f = US]C^f(\Omega_{it}), \end{aligned} \tag{1}$$

where r denotes the real interest rate.[15] Accumulated savings are held at the individual's location of residence. In order to take into account differences in currency purchasing power, the stock of assets is adjusted by real exchange rate x if individuals (re-)migrate. The cost

[15] At the beginning of the working life, the stock of assets of household i is related to unobserved earnings potential as $A_{i0} = \tilde{\alpha}_A \exp(\alpha_i^{MX})$, where $\tilde{\alpha}_A$ is an estimated parameter.

of migration may vary with an individual's age, legal status and previous U.S. experience.[16] In particular, a previous stay in the U.S. may lower the cost of re-migration, for instance because initial information constraints are overcome.[17] When a household head is in Mexico,[18] the household may choose to borrow up to some limit $B(\mathrm{E}[y_{it}^{MX}], \Omega_{it})$ in order to smooth consumption or to finance a migration. Motivated by evidence presented in Figure 2, I let this limit vary by (expected) earnings.[19] I further assume that this borrowing constraint becomes tighter towards the end of life, enforcing a repayment of debt during retirement (see Appendix B for details).[20] The borrowing limit $B(\mathrm{E}[y_{it}^{MX}], \Omega_{it})$ is binding. Hence, assets are constrained by

$$A_{it} \geq -B(\mathrm{E}[y_{it}^{MX}], \Omega_{it}) \qquad \text{at all times.} \tag{2}$$

Equations (1) and (2) summarize an identification problem that arises when both borrowing constraint B and migration cost C are unknown. Since the levels of assets immediately before and after a migration has been paid for are unobserved in available data, C cannot be inferred directly. Hence, it is unclear whether an observed migration has been facilitated by a cost that is low enough to be covered by cash on hand, $(1+r)A_{it-1} + y(\Omega_{it})$, or whether migration costs are in fact higher, while $B > 0$ and households can borrow to partly pay for the migration.

Preferences. Agents derive utility from consumption and location amenities. Utility flows are further adjusted if an individual has family, and depend on where this family resides. With these features in mind, preferences are specified as

$$u_{it} = \left(\left(\phi_f^{\mathbf{l}}\right)^{f_{it}} c_{it} \right)^{\phi_c} \pi_i^l + \varepsilon_{it}^{\mathbf{l}},$$

where $\phi_f^{\mathbf{l}} = \phi_f^{l \neq l^f}$ if families are spatially separated, and $\phi_f^{\mathbf{l}} = \phi_f^{l = l^f}$ if not. Besides a disutility due to spatial separation from family, the scaling of consumption by $\phi_f^{\mathbf{l}}$ captures variation in consumption efficiency that can arise if remittances imply that part of household consump-

[16]Specifically, the cost function is given by $C(\Omega_{it}) = \gamma_0 + \gamma_a a_{it} + \gamma_{undoc}(1 - d_{it}) + \gamma_X \mathbb{1}[X_{it}^{US} > 0]$, with estimated parameters γ_0, γ_a, γ_{undoc} and γ_X.

[17]Bryan et al. (2014) find a higher probability of consecutive rural-urban migrations in Bangladesh after the cost of an initial trip has been covered, and rationalize this with lower information constraints about earning opportunities at the destination. A relaxation of financial constraints is a plausible explanation in the Mexico-U.S. context, where income differentials are known to be large.

[18]Evidence by Banerjee and Munshi (2004) and Laszlo and Santor (2009) suggests that weaker network structures limit credit access in the destination country.

[19]Expected earnings $\mathrm{E}[y_{it}^{MX}] = \alpha_i^l + f^l(a_{it}, X_{it}^{US})$ net of the transitory shock v_{it}^l are more informative about life-time income, and thus likely more relevant to lenders than y_{it}^{MX}.

[20]Default is not observed in my data. However, wider family and social networks in Mexico make it plausible that repayment can be enforced even in case of migration.

tion takes place in a different location than the household head's. In addition, consumption may respond to changes in family status even in the absence of migration. As only relative utility flows in the two locations are identified, π_i^{MX} is normalized to one, so that π_i^{US} becomes the marginal utility from consumption in the U.S. relative to marginal utility from consumption in Mexico. A higher valuation of consumption in Mexico may make temporary migration and asset accumulation in a higher wage country such as the U.S. the optimal choice for agents.[21] In addition to heterogeneous time-constant location preference π_i^{US}, households face location-specific transitory preference shocks $\varepsilon_{it}^{\mathbf{l}}$.[22] These unobserved preference components capture any constant and time-varying valuations of unobserved location characteristics. I assume that u_{it} goes to minus infinity for $c_{it} < 0$, which prevents individuals for whom $(1+r)A_{it-1} + y(\Omega_{it}) + B(\mathrm{E}[y_{it}^{MX}], \Omega_{it}) < C(\Omega_{it})$, i.e. cash on hand plus the maximum obtainable credit does not cover the migration cost, from migrating.

Welfare. After family and legal status have been revealed, the location of both the household head and of dependent family members has been chosen, and agents know the job offers and earnings available to them, consumption is chosen to maximize household welfare subject to the budget constraint (1) and the borrowing constraint (2). The dynamic problem for these choices is given by the Bellman equation

$$V(\Omega_{it}) = \max_{c_{it}, \mathbf{l}_{it}} u_{it}(c_{it}, \Omega_{it}) + \beta \mathrm{E}_t \left[V(\Omega_{it+1}) \right],$$

where β discounts future utility and $\mathrm{E}_t[\cdot]$ denotes expectations given the information available at time t. The laws of motion for the persistent stochastic state variables in Ω_{it} are governed by the transition probabilities $\lambda_w(\Omega_{it})$, $\lambda_{nw}(\Omega_{it})$, $p_{f+}(\Omega_{it})$, $p_{f-}(\Omega_{it})$, $p_{d+}(\Omega_{it})$ and $p_{d-}(\Omega_{it})$, as well as the welfare maximizing choices of c_{it} and $\mathbf{l}_{it}$ subject to (1) and (2). Individuals live until age a^{end}, with $V(\Omega_{it} | a_{it} = a^{end}) = 0$.

4 Estimation

The model is solved backward, and the resulting choice functions are used to simulate migration and consumption behavior of a sample of individuals. I estimate the 94 parameters of

[21] An alternative explanation for non-migration by some individuals despite persistent wage differences across locations is the existence of insurance networks in an individual's home community, which are weakened in case of a migration (as in Munshi and Rosenzweig, 2016). In contrast to location specific marginal utilities from consumption, the existence of insurance networks alone, however, cannot rationalize temporary emigration.

[22] I let $\varepsilon_{it}^{\mathbf{l}}$ be extreme value distributed with cdf $P(\varepsilon \leq x) = \exp(-\exp(-x/\sigma^{\varepsilon}(a_{it})))$, where $\sigma^{\varepsilon}(a_{it})$ is an estimated spread parameter, specified as a linear function of age. Additivity of ε in the utility function, independence and extreme value distribution imply that the location choice probabilities take a logistic form, with value functions in the home and host country as arguments.

the model by indirect inference (Gourieroux et al., 1993), minimizing the distance of 232 moments computed for this simulated sample to their empirical counterparts in the four data sets. As I combine data sets with different sample sizes and partly representing different populations, important econometric issues arise, which are addressed in Section 4.2.

Before that, I discuss parameter identification. The three key assumptions that allow identification despite a rich set of unobserved components in the model are: (1) the rank within the productivity distributions in Mexico and in the U.S. is preserved. This requirement follows from the lack of representative data sets that follow individuals across countries and that have longitudinal earnings information on both sides of the border; (2) agents move based on expected earnings before transitory shocks v_{it}^l are observed; (3) the randomized treatment assignment of Progresa is uncorrelated with the innate preference π_i^l for living in the U.S. This does not exclude that the incentive to migrate varies with treatment status, for instance due to higher incomes for treated households. Conditional on income, however, the preference for moving is orthogonal to the experimental variation in the introduction of the program. In what follows, identification is discussed more comprehensively, with additional details provided in Appendix E

4.1 Identification

Observed outcomes. Most parameters are identified from conditional data moments obtained through auxiliary regressions which are closely related to the respective parameters. To identify parameters governing transitions in family status $(p_{f+}(\Omega), p_{f-}(\Omega))$, legal status $(p_{d+}(\Omega), p_{d-}(\Omega))$ and employment $(\lambda_w(\Omega), \lambda_{nw}(\Omega))$, I match coefficients from OLS regressions of observed transitions in these outcomes on state variables that determine them. Note that due to the endogenous selection of individuals into locations, and thus either Mexican or U.S. samples, these parameters need to be estimated jointly with all other structural parameters within the model. Parameters of the earnings function are identified through regressions of log earnings in Mexico on age indicators, and log earnings of Mexican workers in the U.S. on indicators of age and U.S. experience. The joint distribution of earnings and past migration experience in the two waves of the MxFLS does not allow a separate identification of returns in Mexican earnings to having been to the U.S. on the one hand, and selection into emigration and return migration that is due to a correlation between productivity and the preference for being the U.S. on the other.[23] The flexible specification of unobserved heterogeneity allows

[23]The literature so far has been ambiguous as to whether there are returns to a temporary U.S. migration for Mexican workers: while Reinhold and Thom (2013) do find small positive returns under restrictions on the selection process, Lacuesta (2010) argues that observed earnings differences between Mexican non-migrants and returnees are likely the result of selective emigration.

for the latter, but hence requires that for earnings in Mexico $f^{MX}(a_{it}, X_{it}^{US}) = f^{MX}(a_{it})$.

Unobserved heterogeneity and preferences. The simulation approximates unobserved heterogeneity by a finite mixture, assuming a discrete number of types of individuals, who differ in their preference and productivity. The longitudinal dimension of earnings data in the Mexican Family Life Survey and the U.S. SIPP data identifies the marginal distributions of productivities α_i^{MX} and α_i^{US}. Specifically, heterogeneity in these productivities around their means is identified by quantiles of (within-individual) mean earnings residuals from the abovementioned auxiliary regressions of earnings on age and U.S. experience. The marginal distribution of preferences π_i^{US} for being in the U.S. is pinned down by the distribution of time spent there. In addition, the estimation targets the joint distribution of past migration experience and mean earnings residuals in Mexico from the MxFLS, as well as the joint distribution of time spent in the U.S. and mean earnings residuals in the U.S. from the SIPP. These latter two sets of moments link productivity in the two locations to preferences, and allow for a correlation between these dimensions. In the absence of longitudinal earnings information in Mexico and in the U.S. *for the same individuals*, however, the restriction has to be imposed that the rank within the two productivity distributions be preserved across locations. The average number of trips per migrant by age, in turn, is informative for the spread parameter of transitory shocks to locational preferences. The remaining preference parameters, such as risk aversion, are identified from observed saving and location choices for both household heads and spouses.

Costs and debt limit. Conditional on the stock of assets, the migration cost $C(\Omega_{it})$ can be identified from observed migrations *if access to credit is specified.* To see the importance of credit access, note that a more restrictive model which assumes a debt limit $B = 0$, so that borrowing is ruled out, would attribute observed emigration rates to a lower cost of moving than a model that allows for borrowing. Evidence on the empirical relevance of this bias is provided in Appendix C, suggesting that a more restrictive model without borrowing would underestimate the monetary cost of migration by up to 65 percent.

The MxFLS reports household debt, which can identify the *level* of credit limits. However, based on the evidence shown in Figure 2, the model further allows access to credit to depend on income. This *slope* with respect to income creates a further identification problem given the flexible specification of unobserved heterogeneity: Suppose for instance that high productivity individuals have a high preference for migrating to the U.S., and hence a potentially higher demand for credit to finance migrations. In this case, an observed positive correlation between earnings and debt could either be generated by better credit *access* for individuals with higher earnings (i.e. a positive value for the slope parameter), or by these individuals' higher *demand* for credit. Simple survey covariation as in the MxFLS would be sufficient to identify the income dependence of debt limits in a simpler model that imposes orthogonality between the dimensions of unobserved heterogeneity. Identification thus either requires restrictions on unobserved heterogeneity, or a source of variation in income which is uncorrelated with unobserved preferences.

To avoid additional restrictions, and to keep the model more realistic, I thus exploit the randomized introduction of Progresa cash transfers in Mexico. This program provided continuous income streams, which could be used as a collateral for credit. Specifically, I include the effect of an exogenous variation in income induced by the program on borrowing, which due to the randomization is non-parametrically identified, among the set of moments used in the structural estimation of the model. The identifying assumption here is that the randomized treatment is uncorrelated with individual preferences for residing in the U.S. (π_i^{US}). The average treatment effect of being covered by the program, $\mathrm{E}[loan_i|\mathbb{1}_i^{treated} = 1] - \mathrm{E}[loan_i|\mathbb{1}_i^{treated} = 0]$, is identified by α_1 in an OLS regression of the form

$$loan_i = \alpha_0 + \alpha_1 \mathbb{1}_i^{treated} + \boldsymbol{\alpha_2}' \mathbf{x}_i + u_i, \tag{3}$$

where $\mathbf{x}_i$ controls for a number of household characteristics.[24] In this sample of fairly poor households, the mean monthly transfer amount of 260.32 pesos (51.14 PPP adjusted USD) corresponds to 27.8 percent of household heads' average earnings in control villages. This sizeable exogenous variation in income helps to pin down the income dependence of borrowing limits. The estimates reported in Table 2 show no evidence for an increase in the extensive margin of credit take-up, whereas the average *level* of (positive) loans taken within the past 6 months increases by 0.43 log points (from a mean of 203.64 PPP adjusted USD in control communities). Appendix A provides additional details, including the full distribution of loan take-up, and pre-program differences across communities. After introducing treatment status as an additional state variable, this treatment effect is a moment the model can generate, and that is included in the structural estimation. Indirect inference estimation does not actually require a consistent estimate $\hat{\alpha}_1$, as (3) only serves as an auxiliary regression. The importance rather lies with the income variation being unrelated to location preferences. Since for a given set of parameters, and conditional on income and other observables, the model implies a demand for credit, the covariation of income and observed borrowing captured by $\hat{\alpha}_1$ identifies the income dependence of credit access.[25]

[24] As explained in Section 2, the sample is restricted to eligible households with children up to the age of 14 attending school, for whom Progresa de facto was an unconditional transfer, as in control communities over 97 percent of these children attended school even in the absence of the program.

[25] Again identification further requires that for some individuals demand exceeds the constraint, i.e. that the constraint is binding, which the simulations in Section 5 show to be the case. Adda and Eaton (1998) use a similar strategy to identify constraints to sovereign debt.

Table 2: Average treatment effect of the program on loans taken within 6 months.

	(1) loan> 0	(2) log(loan amount in USD)
$\mathbb{1}^{treated}$	0.00139	0.432
	(0.00517)	(0.196)
Observations	6490	186

Note.— Progresa evaluation data, November 1998. The sample includes eligible male household heads aged 16-64. Dependent variable: loans taken within past 6 months. ATE identified by OLS, controlling for age, employment status, marital status, household size (indicators for 1, ...9, 10+ members), number of rooms (indicators for 1, ...4, 5+ rooms) and land owned (indicators for 1, ..., 9, 10+ hectares). Standard errors are clustered at the municipality level.

4.2 Data Combination

Two issues arise when combining different data sources as required for the estimation of this model: first, two of the samples used (the MMP and Progresa samples) are non-representative. Second, all four data sets have different sample sizes and thus provide moments of different precision. I address these in turn.

Representativeness. Both the communities sampled by the MMP and by Progresa are predominantly low-income villages. The model presented in Section 3, however, was chosen as a description of the entire population of Mexican-born male household heads without tertiary education, as are moments generated from the Mexican Family Life Survey and the U.S. SIPP data. The model accounts for selection into locations where the different surveys are collected, and the simulated moments used for estimation are throughout constructed for individuals satisfying the sample selection and treatment criteria in terms of observable characteristics. For instance, moments are constructed for simulated agents at an age that is drawn from the empirical age distribution in each survey, and who at that age are in the location where the data are collected. In the case of Progresa, a further selection criterion is to have dependent family that resides in Mexico (whereas the head might not).

Beyond these observed characteristics, the dimensions along which the samples differ are not clear a priori. The higher poverty level among households covered by Progresa, however, is the most obvious deviation from representativeness, while the main critique against the MMP in the literature is its bias toward communities with a strong history of sending migrants to the U.S.[26] Lower earnings and a higher migration propensity correspond

[26]See e.g. Orrenius and Zavodny (2005), Hanson (2006), McKenzie and Rapoport (2007) and Fernández-Huertas Moraga (2011). Some of these authors maintain that while the MMP might not be a good representation of the Mexican population as a whole, it probably is a good approximation of the population of Mexican migrant sending households. Given that interviews take place in Mexico, however, the latter certainly is a relief only to the extent that the emigration and return migration process is modeled.

closely to the dimensions of unobserved heterogeneity in the model. To account for this non-representativeness, I thus allow for different weights of the unobserved heterogeneity types in the simulation.

To be precise, let τ index the T discrete types of simulated individuals used to approximated unobserved heterogeneity in the population. In the model, each of these types is associated with a 3-tuple of preference for the U.S. (π_τ^{US}), productivity in Mexico (α_τ^{MX}) and productivity in the U.S. (α_τ^{US}). The points of support for these unobserved vectors, $(\pi_\tau^{US}, \alpha_\tau^{MX}, \alpha_\tau^{US})$, $\tau \in \{1, ..., T\}$, are identified from the joint distribution of earnings and migration patterns observed in the representative samples of the MxFLS and the SIPP, as explained above. To account for different earnings and a different propensity to migrate conditional on observables among Mexicans sampled by the MMP and Progresa, however, I allow for separate sets of weights $\{\omega_1^{MMP}, ..., \omega_T^{MMP}\}$ and $\{\omega_1^{Progresa}, ..., \omega_T^{Progresa}\}$ in the construction of simulated moments that have their empirical counterparts in the MMP and Progresa samples, respectively. This allows, for instance, for low productivity types having stronger weights in moments with an empirical counterpart in the Progresa sample. Similarly, if migrant networks from MMP communities reduce the utility cost of residing in the U.S. conditional on observable state variables, then types with a higher π_τ^{US} will receive a higher weight in simulated moments to be matched with data moments from the MMP. This not only allows for different productivity or preference *levels* across samples, but the entire joint *distribution* of unobserved heterogeneity may be different, allowing also for different levels of inequality. Weights are estimated jointly with all other parameters. Note that only the weights vary across samples, whereas the points of support are fixed, and are identified from the two representative samples. Identification of the weights thus can be achieved by targeting the distribution of one outcome per set of weights only.[27]

Different sample sizes. A different concern arises irrespective of the representativeness of samples. All four data sets used here have different sample sizes and yield moments of different precision. If all data moments needed for identification were observed from the same source with sample size N, Gourieroux et al.'s (1993) indirect inference estimator would converge at a rate $\sqrt{N}$ (adjusted by the size of the simulated sample, as detailed below). My estimation, however, uses data moments from four samples $\varsigma \in \{MMP, MxFLS, SIPP, Progresa\}$ of different sizes N_ς. While consistency of the estimator is unaffected by the use of multiple samples, the derivation of the asymptotic distribution requires an assumption on the rate at which these samples increase.

In line with Angrist and Krueger (1992) and Arellano and Meghir's (1992) discussion

[27] I include deciles of the earnings distribution from the Progresa sample, and deciles of the propensity to be in the U.S. from the MMP sample as additional moments in the estimation.

of the two sample instrumental variables estimator, assume that sample sizes increase at proportional rates, and let simulated sample sizes N_ς^s increase at a rate which satisfies $\lim_{N_\varsigma \to \infty, N_\varsigma^s \to \infty}(N_\varsigma / N_\varsigma^s) = n_\varsigma^s$, with $0 < n_\varsigma^s < \infty$. The indirect inference estimator $\hat{\theta}$ for a vector of parameters θ minimizes criterion $\Gamma(\vartheta) = D(\vartheta)' W D(\vartheta)$, where $D(\vartheta) = m^d - m^s(\vartheta)$ is the difference between a vector of observed data moments m^d and the corresponding moments $m^s(\vartheta)$ simulated from the model with structural parameters ϑ, and W is a weighting matrix. Importantly, the observed moment vector may be a collection of moments calculated from different data samples, such that $m^d = (m^d_{MMP}, m^d_{MxFLS}, m^d_{SIPP}, m^d_{Progresa})'$. The moments used in this paper are asymptotically normally distributed. Hence, under the additional assumptions listed in Appendix D, where I provide a derivation of this result,

$$\sqrt{N}(\hat{\theta} - \theta) \xrightarrow{d} \mathcal{N}\left(0, \left(\frac{\partial D'}{\partial \vartheta}\bigg|_{\hat{\theta}} W \frac{\partial D}{\partial \vartheta'}\bigg|_{\hat{\theta}}\right)^{-1} \right.$$
$$\left. \cdot \left(\sum_{\varsigma} N(1 + n_\varsigma^s) \frac{\partial D_\varsigma'}{\partial \vartheta}\bigg|_{\hat{\theta}} W_\varsigma \mathrm{var}\left(m_\varsigma^d\right) W_\varsigma' \frac{\partial D_\varsigma}{\partial \vartheta'}\bigg|_{\hat{\theta}}\right) \left(\frac{\partial D'}{\partial \vartheta}\bigg|_{\hat{\theta}} W \frac{\partial D}{\partial \vartheta'}\bigg|_{\hat{\theta}}\right)^{-1} \right),$$

with $D_\varsigma(\hat{\theta}) = m_\varsigma^d - m_\varsigma^s(\hat{\theta})$, $N = \sum_\varsigma N_\varsigma$, and blocks W_ς on the diagonal of weighting matrix W, with one block of weights for the moments from each sample ς.

5 Results

5.1 Model Fit

The model was chosen to mirror migration choices in a context where many migrants choose to return and possibly re-migrate at a later stage. In this section I show how well the model is able to replicate these patterns. The left panel of Figure 5a displays the distribution of the number of migrations undertaken up until the time individuals were surveyed by the Mexican Migration Project.[28] For comparison, the right panel of Figure 5a shows the same distribution in the population simulated by the model. Similarly, Figure 5b shows the empirical and simulated distributions of the time migrants have spent in the U.S. The model matches these distributions well, as it does for the average treatment effect of Progresa transfers on borrowing (see Table 15 at the end of Appendix E, where the fit for the full set of moments is listed). As discussed earlier, a rise in household earnings has at least two counteracting effects on the propensity of individuals to emigrate: While staying becomes relatively more

[28]Note that this is weakly less than the total number of migrations during an individual's life cycle, which Figure 1a attempted to capture by restricting the sample to individuals aged 65 or older.

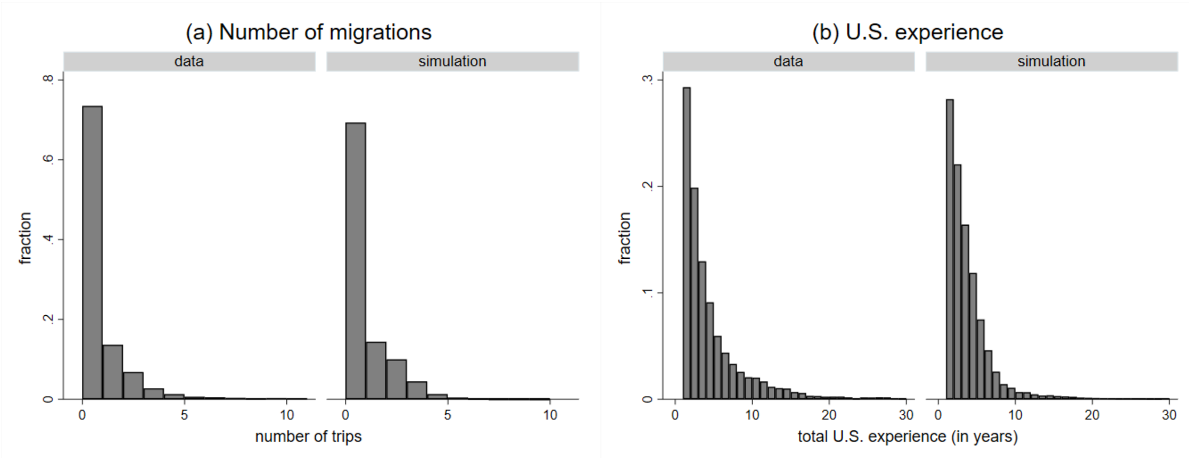


Figure 5: Model fit: Number of migrations and time in the U.S. Distributions of (a) the number of migrations in the MMP data at the time of the survey and the corresponding distribution in the population simulated by the model; and (b) total time spent in the U.S., as reported in the MMP data and the simulated sample. Model predictions are based on 40,000 simulated individuals, drawn from the MMP's age distribution at the time of the survey and estimated weights used in the construction of moments with empirical counterparts in the MMP.

attractive as earnings and thus the opportunity cost of migration rise, higher earnings may help to overcome binding liquidity constraints and facilitate emigration to a still higher paying destination, or one where an individual desires to move to for non-economic reasons. While in the absence of financial constraints the above model would unambiguously predict a negative effect of higher earnings in the country of origin on emigration, existing evidence from reduced form studies points toward a positive net effect in many contexts. The most directly comparable estimates are those by Angelucci (2015), who evaluates the average treatment effect of Progresa on the propensity to emigrate in a linear probability model and finds that it raises the emigration rate by about 50 percent. As the treatment effect on emigration is not used in the estimation of the model in Section 3, a comparison to Angelucci's estimate may serve as an additional credibility check of the model. To do this, I simulate a population where I draw individuals with dependent family from the age distribution of eligible households' heads in the Progresa evaluation data, and apply Angelucci's age restriction (≤ 40). After using the estimated unobserved heterogeneity weights for this sample, the introduction of a Progresa equivalent transfer is predicted to increase the emigration rate by 36 percent, which is statistically indistinguishable from Angelucci's estimate (difference has a p-value 0.86).[29] The model's predictions for the effect of a rise in earnings are presented in more detail in Section 5.3. In particular, the model also aligns with Angelucci's results in predicting an inverted U-shaped effect along the wealth distribution. This similarity of

[29] Own calculation based on estimates reported in the first column of Table 1 of Angelucci (2015).

estimates obtained via two very different econometric approaches is reassuring.

5.2 Estimates

The model has 94 estimated parameters. I focus here on a subset, in particular on estimates describing preferences, migration costs and access to credit. A full list of the structural parameter estimates is provided in Appendix F.

Preferences. Utility in the model is derived from consumption, family status and family location, as well as from locational amenities that may be valued differently across individuals. Everything else equal, and for individuals without dependent family, preferences π^{US} for being in the U.S. vary from a utility gain of 30 percent ($\pi_3^{US} = 1.299$) to a penalty of 40 percent ($\pi_4^{US} = 0.603$), see Table 3.[30] Per period utility flows are adjusted by whether an individual has dependent family members, and by whether they reside in the same location. The estimate of $\phi_f^{l=l^f}$ ($\phi_f^{l\neq l^f}$) larger (smaller) than one means that individuals derive positive utility (suffer a utility loss) from having family if this family resides in the same (a different) location. In the model, this rationalizes the observation that individuals are much more likely to migrate at younger ages, when they do not (yet) have dependent family. The estimate of ϕ_c implies a decreasing marginal utility of consumption, with a risk aversion of 0.79.[31]

Borrowing limit. Apart from a debt limit that becomes tighter towards the end of life and ensures repayment, households face a constraint to the maximum amount of debt they can hold that is related to their expected earnings (see Section 3 and Appendix B for details). This part of the constraint, which is specified as a linear function of expected earnings, is predicted to be the binding constraint in most cases. The estimates listed in Table 3 imply that only households with half-yearly earnings of at least $-(\delta_0 \cdot 1,000\$)/\delta_y \approx 1,028$ USD have access to credit, with the debt limit rising by $\delta_y/2 \approx 1.3$ USD for every additional USD per year earned.

Migration costs. The monetary cost of migration increases with age, and migrants face a lower cost if having been to the U.S. previously, but a higher one for border crossings without a U.S. permit. For instance, the cost for 30-year-old household heads without a U.S. visa who have previously been to the U.S. amounts to $5,757 + 30 \cdot 54 - 3,211 + 2,156 = 6,322$ USD. The estimate for the extra cost of an undocumented migration, γ_{undoc} includes both the direct smuggler cost and other monetary costs associated with an undocumented arrival in the U.S.

[30] The types in Table 3 are ordered by their productivity, see Tables 20 and 21 in the Appendix.

[31] This is comparable to Imai and Keane (2004) who estimate it at 0.74. Allowing for heterogeneous risk preferences, Belzil et al. (2017) report a mean value for relative risk aversion of 0.73.

Table 3: Preference, borrowing constraint and migration cost parameters.

Parameter	Point estimate	Standard error
Preferences: $u_{it} = ((f_{it}\phi_f^{\mathbb{I}} + (1-f_{it}))c_{it})^{\phi_c}\pi_i^l + \varepsilon_{it}^{\mathbb{I}}$		
preference of type 1 for the U.S. (π_1^{US})	1.291	(0.246)
preference of type 2 for the U.S. (π_2^{US})	0.745	(0.098)
preference of type 3 for the U.S. (π_3^{US})	1.299	(0.083)
preference of type 4 for the U.S. (π_4^{US})	0.603	(0.036)
returns to consumption (ϕ_c)	0.207	(0.018)
scaling for spatial separation from family ($\phi_f^{l\neq l^f}$)	0.409	(0.030)
scaling for family in same location ($\phi_f^{l=l^f}$)	5.940	(0.230)
Borrowing limit: $B(\mathrm{E}[y_{it}], \Omega_{it}) = \min\{\delta_0 + \delta_y \mathrm{E}[y_{it}], \cdot\}$ (in 1,000USD)		
intercept (δ_0)	-2.685	(0.094)
effect of biannual earnings (δ_y)	2.613	(0.060)
Migration cost: $C(\Omega_{it}) = \gamma_0 + \gamma_a a_{it} + \gamma_{undoc}(1-d_{it}) + \gamma_X \mathbb{1}[X_{it}^{US} > 0]$ (in 1,000USD)		
intercept (γ_0)	5.757	(0.172)
effect of age (γ_a)	0.054	(0.001)
effect of having been to the U.S. (γ_X)	-3.211	(0.254)
extra cost of undocumented migration (γ_{undoc})	2.156	(0.148)

Note.— Model parameters characterising preferences, access to credit and migration costs estimated by simulated minimum distance estimation based on 40,000 simulated individuals $\times$ 50 years $\times$ 2 seasons. See Section 4.2 for details on the computation of standard errors.

A full list of the estimated model parameters is provided in Appendix F. Where, for instance, Tables 20 and 21 show that both in Mexico and the in U.S. earnings profiles are concave over an individual's life cycle. In addition, U.S. earnings exhibit large returns to U.S. experience, though again at a decreasing rate. This corresponds to the patterns that have been documented for many different migration contexts (see e.g. Barth et al., 2004; Lubotsky, 2007; Green and Worswick, 2012).

5.3 Effects of a Rise in Earnings in the Country of Origin

I use the estimated model to analyze the effect of higher earnings in a country of origin on migration dynamics. Identification of short-run net effects of income on emigration can be achieved by reduced form estimations if an exogenous variation in earnings can be exploited. Beyond this extensive margin, however, an increase in earnings also affects migration on the intensive margin of migration duration, as well as the propensity of individuals to move back and forth repeatedly, and the selection of those who return. An understanding of these dynamic choices is important: Given that many Mexican migrants stay in the U.S. only temporarily, it is a priori unclear whether a positive effect on the propensity to emigrate implies a one-to-one increase in the stock of migrants residing in the U.S. Furthermore, the selection of both emigrants and return migrants is likely to respond to changes in economic conditions at the origin. Available data that capture exogenous variation in income—such as the Progresa evaluation data—do not provide information on post-emigration decisions like whether and when migrants return. I thus use additional information on economic outcomes and choices like saving and migration decisions from data sets from both sides of the border to identify preference parameters and constraints in the behavioral model presented in Section 3. This allows me to investigate how strongly different margins of migration are affected by earnings levels, including migration durations and repeat migration.

Return migration. Whereas emigration, as well as the number of migrations are constrained by the cost of moving to the U.S., the decision to return is affected by migration costs more indirectly, in that migrants may anticipate a potential desire to re-migrate in the future. This could be the case, for instance, if a job in Mexico is lost. Instead, the decision to return is primarily driven by preference parameters, which determine the dis-utility from staying abroad, as well as the value attributed to savings accumulated abroad if consumed in the home country.

I use the model to simulate the effect of a 10 percent increase in Mexican earnings on return migration. This rise in earnings on average covers about 10.9 percent of the cost of a legal migration without family, or equivalently 24.7 percent of the estimated extra cost if a migrant attempts to cross the border without legal documentation. A rise in expected earnings at origin not only raises the opportunity cost of staying abroad in terms of origin earnings forgone, but the value of being in the country of origin is boosted further because individuals know that the future option to emigrate will be more easily affordable if desired. Both these channels are likely to raise return migration and shorten migration durations among immigrants in the U.S.

The left-hand graph of Figure 6 shows the survival rates of immigrants in the U.S., that is, the fraction of initial arrivals remaining in the country by years since immigration. Whereas the solid curve represents the survival rate at baseline, the dashed profile shows the reduction in migration duration if earnings in Mexico were 10 percent higher, which shortens the average time continuously spent in the U.S. by more than half a year, or 4.4 percent. This effect, however, may partly be driven by compositional changes. Figure 6b thus isolates the pure behavioral effect by restricting the sample to those who are predicted to migrate under either scenario, with a reduction in average time spent in the U.S. for this sub-population of 10.3 percent. The reason for the smaller effect of higher earnings in Mexico for the full population is that at baseline it includes more individuals who are on the margin of migrating. These individuals tend to stay for a shorter time period in the U.S., but do not migrate at all under higher earnings in Mexico. Such migrants are excluded in Figure

6b to isolate the behavioral response of migrants net of composition changes.[32]

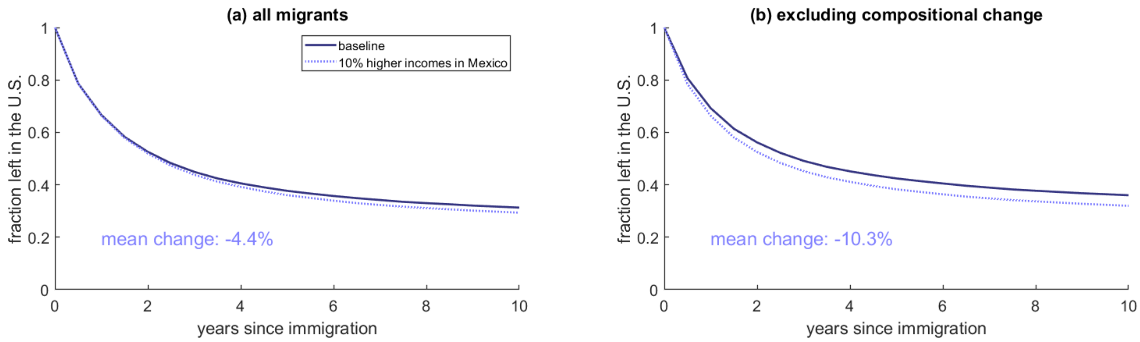


Figure 6: Fraction left in the U.S. Survival rates in the U.S. under different earnings levels in Mexico of (a) all Mexican immigrants, (b) Mexicans who would have migrated under both earnings levels. Model prediction based on 40,000 simulated individuals.

Repeat migration. Figure 1 showed that repeat migration is a common phenomenon between Mexico and the U.S. In the model used here, repeated migrations can be driven by various factors. For instance, an immigrant in the U.S. who has accumulated sufficient savings may find it worthwhile—given expectations about employment and other outcomes—to return and enjoy a higher utility from consumption in Mexico where other family members live. If later on that returnee loses a job and re-employment probabilities in Mexico are relatively low, a re-migration may be the optimal choice. Similarly, shocks to preferences, earnings, family or legal status may trigger repeated migrations. Furthermore, seasonal variation in aggregate labor demand may lead to multiple trips. The estimates in Table 3 indicate that the cost for these subsequent migrations will be lower.

An increase in sending country earnings makes migrations more affordable. Hence, apart from increasing the appeal of spending time in the origin country, such a change enhances the capacity of individuals to adjust to changing personal and economic conditions, including employment opportunities. For instance, immigrants in the U.S. losing a job will be less reluctant to return to Mexico, knowing that a re-migration the following spring, when more jobs will be on offer, is affordable. Figure 7, which shows the distribution of the number of migrations, illustrates this for an increase in Mexican earnings by 10 percent, and separately for (a) all migrations, and (b) for only those individuals who migrate at least once under either regime, hence eliminating compositional changes by looking at the same group of individuals throughout. At baseline, the average number of migrations over an individual's working life and conditional on having ever migrated is about two.[33] An increase in earnings

[32]Unreported results further show that the effect is stronger for migrants who arrive without legal documentation to the U.S. and who do not have family at the time of migration.

[33]Note that this is different from the distribution displayed in Figure 1a, which is drawn from the non-representative MMP data, and is conditional on migrants having returned.

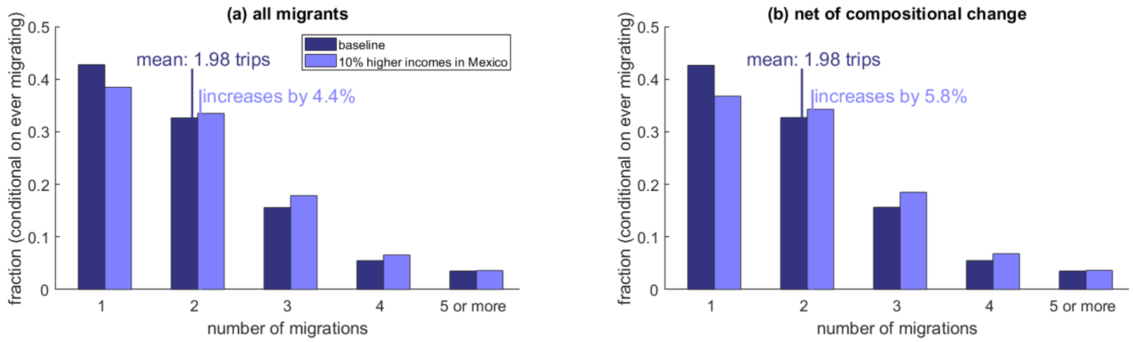


Figure 7: Effect of higher origin country earnings on repeated migrations. Number of migrations under different earnings levels in Mexico, considering (a) all individuals with at least one migration under the respective scenario, and (b) individuals with at least one migration in either of the cases considered. Model prediction based on 40,000 simulated individuals.

by 10 percent shifts this distribution outward, increasing the average number of migrations by 4.4 percent. Part of the behavioral change among individuals who would have migrated under both scenarios may be obscured by compositional changes as additional individuals can afford to migrate and others may prefer to stay in Mexico if earnings are higher. To abstract from these selection effects, the right-hand graph shows the change in the number of migrations only for those who are predicted to migrate at least once under either scenario. The purely behavioral change in response to a 10 percent increase in earnings in Mexico is in fact slightly larger (5.8 percent). This shows that rather than by compositional changes, the effect is driven by the response of individuals who would have migrated even in the absence of the program (Figure 7b), while compositional changes slightly offset this shift in the distribution (Figure 7a).

Differences by productivity. The effects described vary across the earnings distribution. Table 4 hence displays outcomes separately for individuals with below median productivity levels and for those with productivity above the median. Columns (1) and (3) show outcomes at baseline, whereas columns (2) and (4) show the same outcomes in the counterfactual situation with 10 percent higher earnings levels in Mexico.[34] The first row shows that higher origin country incomes lead to more short-term migrations, in particular among low-income individuals, whereas the increase in the average number of trips shown in Figure 7 is driven by high-earners. Row (c) shows that changes in the fraction of migrants taking their family along are negligible. Low-income individuals, who are more often financially constrained, gain better access to credit under higher incomes and use this to finance migration costs. Higher-income individuals, who already at baseline have better access to credit instead do not raise their borrowing (row d).

[34]The table displays total aggregate effects within these broad productivity levels, which includes compositional changes that Figures 6b and 7b eliminate.

Table 4: Effect of an increase in origin country earnings.

	(1)	(2)	(3)	(4)
	Below median productivity		Above median productivity	
	baseline	10% higher earnings	baseline	10% higher earnings
(a) Migration duration	10.70	8.38	12.11	11.62
(b) Number of migrations	1.68	1.60	1.98	2.07
(c) Share with family in the U.S.	0.44	0.44	0.58	0.58
(d) Loan taken per trip	1272.33	1395.79	1577.99	1564.22
(e) Saving abroad per trip	2261.04	1778.77	6136.02	5820.17

Note.— Counterfactual outcomes as predicted by the model under 10 percent higher origin country earnings, separately for individuals with below and above median productivity. Simulation based on 40,000 agents $\times$ 50 years.
* Accumulated savings abroad after migration costs have been paid.

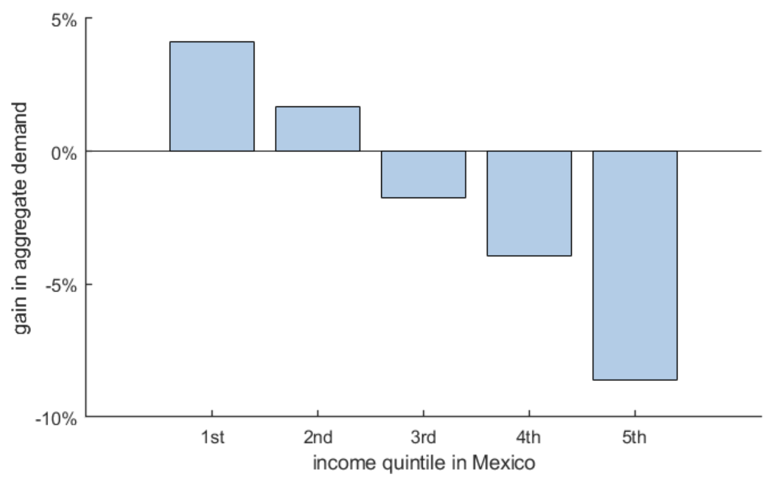
The last row of Table 4 shows that individuals of all income levels reduce their saving abroad when knowing that incomes in Mexico after a return are higher. This reflects both a reduced urge to repatriate savings to Mexico when earnings there are higher, and that migration becomes affordable for lower-productivity individuals who achieve lower earnings in the U.S. Nonetheless, as many of these additional migrants later return to Mexico, aggregate consumption expenditure in Mexico may in fact increase. The next paragraph investigates this further.

Consumption expenditure in Mexico. A margin of migrant behavior that the above model is well-suited to address is the response in individual savings. In light of the temporary nature of many migrations and the higher earnings level in the U.S., an important outcome from a Mexican perspective is the contribution of repatriated savings to the local demand for goods and services in Mexico.[35] Hence, a policy relevant question to ask is whether an increase in earnings in Mexico can raise domestic demand above and beyond this change in earnings, by facilitating migrations that would not have taken place otherwise. While some migrations that have been enabled by higher earnings may be very long or even permanent, so that individuals consume most of their wealth in the U.S.—including assets that have been accumulated in Mexico prior to migration—, others may return with a stock of assets larger than what they owned before emigrating. To evaluate the effect on aggregate expenditure in Mexico, I simulate the same scenario of 10 percent higher earnings in Mexico as before. I then compute the resulting discounted cumulative earnings increase over time, as well as the change in average discounted cumulative consumption (net of migration costs) by individuals residing in Mexico. Figure 8 shows the difference between these two (as a percentage of consumption at baseline), separately for different quintiles of the earnings distribution. The

[35] That price levels and expenditure in the country of origin matter also for migrants' choices in the country of destination has been documented recently in a paper by Albert and Monras (2019).

model predicts that for low-income Mexicans, repatriated savings indeed make up for forgone domestic consumption by long-term emigrants, raising aggregate consumption by 4.1 percent beyond the rise in earnings for the lowest earnings quintile. A non-targeted policy raising earnings across the board, on the other hand, would leave a slightly negative effect of -1.7 percent on aggregate consumption in Mexico.

Figure 8: Effect of higher earnings on expenditure in Mexico.



Effect of 10 percent higher earnings in Mexico on discounted cumulative aggregate consumption (above and beyond the change in earnings and net of migration costs) along the earnings distribution. Changes are expressed as a percentage of consumption at baseline. Model prediction based on 40,000 simulated individuals.

Constraints versus opportunity costs. Any measured response in emigration to a change in country of origin earnings is a combination of two counteracting effects. On the one hand, an increase in earnings in a migrant's country of origin may help overcome financial constraints to migration. On the other hand, these higher earnings raise the opportunity cost of moving abroad. A priori, the net effect is unknown, though the importance of financial constraints have been documented for various contexts (see for instance Angelucci, 2015; Bazzi, 2017). A disentangling of the two mechanisms requires a modeling of migration jointly with savings choices, and the use of information on both. Apart from the analysis of dynamic effects, my model of asset accumulation and migration choices serves this purpose. I use the model to predict the changes in the fraction of individuals residing in Mexico who in any given period would like to move to the U.S. if earnings in Mexico were higher. Figure 9a shows these shares at baseline (solid line) along the wealth distribution, indicating that the desire to emigrate is highest among individuals at the lower end of the distribution. The dashed line shows the changes under a counterfactual scenario of a 10 percent higher earnings level in Mexico. While reducing the desire to emigrate, the rise in earnings also decreases the share of potential migrants who face a binding constraint. Figure 9b reveals that for Mexicans at the very low end of the wealth distribution, the simulated rise in earnings levels by 10 percent is insufficient to overcome financial constraints. At intermediate wealth levels, however, the share of individuals who are constrained among those who wish to migrate is reduced, with a total average reduction by 3.7 percentage points.[36] To the extent that there are multiplier effects due to positive spillovers across households within a community, the effects in Figure 9 underestimate the true effect of a rise in earnings. The net effect is

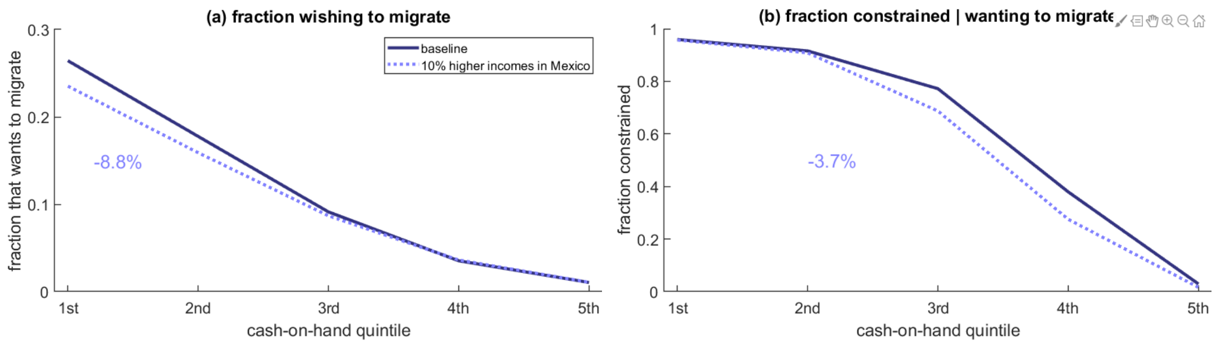


Figure 9: Constraints versus opportunity costs. The figure shows (a) the fraction of Mexican household heads who would want to move to the U.S. in a given year, and (b) the fraction among the former that faces a binding financial constraint, each along the unconditional distribution of cash-on-hand. Model prediction based on 40,000 simulated individuals.

shown in Figure 10a. The inverted U-shape along the wealth distribution of the effect on the fraction leaving under higher Mexican earnings is in line with the pattern documented by Angelucci (2015) in an evaluation of Progresa cash transfers. Note that the model is estimated using data of non-tertiary educated Mexicans only, so that the pattern in Figure 10a does *not* imply an overall positive selection of Mexican emigrants.[37] The same increase in earnings levels in Mexico raises annual return migration among migrants in the U.S. by 7.8 percent, which translates into the reduction in migration duration illustrated in Figure 6 above. Distinguishing cash-on-hand quintiles as before reveals that the effect concentrates in the center and lower part of the wealth distribution (Figure 10b).

6 Conclusion

Earnings levels in a migrant's country of origin affect both the desire and the capability of individuals to migrate. Furthermore, a change in sending country earnings not only has a

[36]Recall that migration costs are not uniform, but vary across individuals depending on their age, legal status and previous migration experience.

[37]The selection of migrants to the U.S. has received attention not least due to their fiscal contribution (see e.g. Auerbach and Oreopoulos, 2000), and role of selection for labor market effects on natives (Llull, 2018). The selection of migrants into different destinations is analyzed for instance by Bertoli et al. (2013).

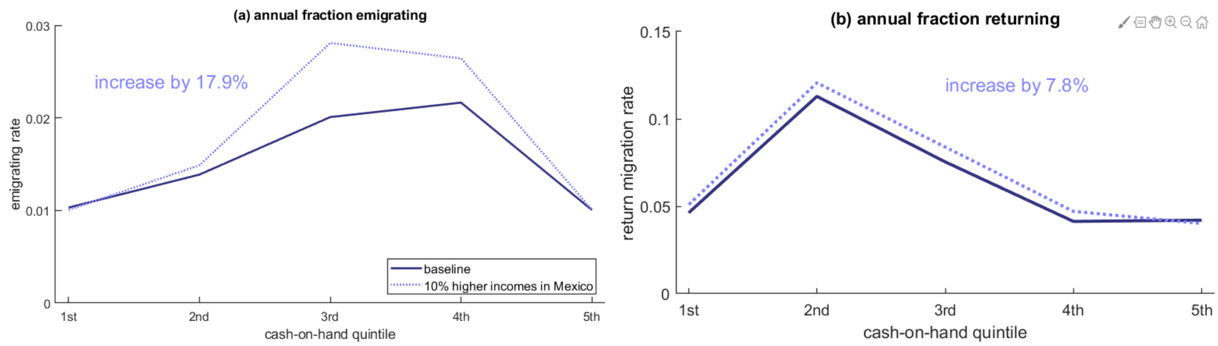


Figure 10: Effect of higher origin country earnings on emigration. The figure shows the fraction of Mexican household heads (a) emigrating to, and (b) returning from the U.S. per year along the distribution of cash-on-hand. Model prediction based on 40,000 simulated individuals.

short-term effect on the probability to emigrate, but also affects the more dynamic aspects of migration, like migration duration and the propensity to migrate back and forth repeatedly, as well as other choices such as savings behavior. Each of these depends on the prevalence of financial constraints and whether agents can borrow in order to finance a migration.

This paper shows that the negative effect of earnings in Mexico on the desire to migrate is dominated by a better affordability of migration, and raises both the emigration rate and the number of trips per migrant. This contrasts with the prediction of models that abstract from asset accumulation and financial constraints, but is well in line with previous reduced form estimations. Understanding the mechanism behind any measured net effect is important for an appreciation of growth enhancing policies in low and middle-income countries with an eye on their longer-term implications for the extent and permanence of migrations. My results predict that for poor individuals higher earnings may well lead to a more than proportional increase in domestic consumption expenditure, financed by repatriated savings of new emigrants who are likely to move only temporarily.

I explicitly consider that part of the monetary cost of migration may be covered by loans, up to an unobserved limit. To identify the model's parameters, I use a combination of panel data sets from Mexico and the U.S., including randomized variation in income induced by a policy experiment. This experimental variation allows the identification of income dependent credit access despite the possibility that the preference for migration and thus also the demand for credit may be related to an individual's earnings capacity. My results suggest that borrowing limits and hence the ability to migrate is indeed strongly and positively related to income. Whereas the economic literature on temporary migration largely has focused on the effects of economic outcomes in the host country on the decision to return, this paper suggests that economic conditions in a migrant's country of origin may have to be taken more strongly into account in future analyses of migrant behavior.

References

Adda, J. and Eaton, J. (1998). Borrowing with Unobserved Liquidity Constraints: Structural Estimation with an Application to Sovereign Debt.

Albert, C. and Monras, J. (2019). Immigration and Spatial Equilibrium: the Role of Expenditures in the Country of Origin.

Angelucci, M. (2015). Migration and Financial Constraints: Evidence from Mexico. *Review of Economics and Statistics*, 97(1):224–228.

Angrist, J. and Krueger, A. (1992). The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables with Moments from Two Samples. *Journal of the American Statistical Association*, 87(418):328–336.

Arellano, M. and Meghir, C. (1992). Female Labour Supply and On-the-Job Search: An Empirical Model Estimated Using Complementary Data Sets. *Review of Economic Studies*, 59(3):537–559.

Attanasio, O., Meghir, C., and Santiago, A. (2012). Education Choices in Mexico: Using a Structural Model and a Randomized Experiment to Evaluate PROGRESA. *Review of Economic Studies*, 79(1):37–66.

Auerbach, A. and Oreopoulos, P. (2000). The Fiscal Effect of U.S. Immigration: A Generational-Accounting Perspective. *Tax Policy and the Economy*, 14:123–156.

Bandiera, O., Rasul, I., and Viarengo, M. (2013). The Making of Modern America: Migratory Flows in the Age of Mass Migration. *Journal of Development Economics*, 102:23–47.

Banerjee, A. and Munshi, K. (2004). How Efficiently is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur. *The Review of Economic Studies*, 71(1):19–42.

Barth, E., Bratsberg, B., and Raaum, O. (2004). Identifying Earnings Assimilation of Immigrants under Changing Macroeconomic Conditions. *Scandinavian Journal of Economics*, 106(1):1–22.

Bazzi, S. (2017). Wealth Heterogeneity and the Income Elasticity of Migration. *American Economic Journal: Applied Economics*, 9(2):219–55.

Bazzi, S., Burns, S., Hanson, G., Roberts, B., and Whitley, J. (2018). Deterring Illegal Entry: Migrant Sanctions and Recidivism in Border Apprehensions. *NBER Working Paper*, 25100.

Bellemare, C. (2007). A life-cycle model of outmigration and economic assimilation of immigrants in Germany. *European Economic Review*, 51(3):553–576.

Bertoli, S., Fernández-Huertas Moraga, J., and Ortega, F. (2013). Crossing the border: Self-selection, earnings and individual migration decisions. *Journal of Development Economics*, 101.

Bryan, G., Chowdhury, S., and Mobarak, A. M. (2014). Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. *Econometrica*, 82(5):1671–1748.

Bryan, G. and Morten, M. (forthcoming). The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy*.

Buchinsky, M., Gotlibovski, C., and Lifshitz, O. (2014). Residential Location, Work Location, and Labor Market Outcomes of Immigrants in Israel. *Econometrica*, 82(3):995–1054.

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

Clemens, M. (2014). Does Development Reduce Migration? In Lucas, R. E., editor, *International Handbook on Migration and Economic Development*, chapter 6, pages 152–185. Edward Elgar Publishing, Lonon.

Colussi, A. (2003). Migrants' Networks: An Estimable Model of Illegal Mexican Immigration. Job Market Paper, University of Pennsylvania.

DellaVigna, S., Lindner, A., Reizer, B., and Schmieder, J. (2017). Reference-dependent Job Search: Evidence from Hungary. *Quarterly Journal of Economics*, 132(4):1969–2018.

Djajić, S., Kırdar, M., and Vinogradova, A. (2016). Source-country Earnings and Emigration. *Journal of International Economics*, 99:46–67.

Dustmann, C. and Görlach, J.-S. (2016). The Economics of Temporary Migrations. *Journal of Economic Literature*, 54(1):98–136.

Dustmann, C. and Okatenko, A. (2014). Out-migration, wealth constraints, and the quality of local amenities. *Journal of Development Economics*, 110:52–63.

Fernández-Huertas Moraga, J. (2011). New Evidence on Emigrant Selection. *Review of Economics and Statistics*, 93(1):72–96.

Friebel, G. and Guriev, S. (2006). Smuggling Humans: A Theory of Debt-Financed Migration. *Journal of the European Economic Association*, 4(6):1085–1111.

Gathmann, C. (2008). Effects of enforcement on illegal markets: Evidence from migrant smuggling along the southwestern border. *Journal of Public Economics*, 92(10):1926–1941.

Gemici, A. (2011). Family Migration and Labor Market Outcomes.

Girsberger, E. M. (2017). Migration, Education and Work Opportunities. *IZA Discussion Paper No. 11028*.

Gole, T. and Quinn, S. (2016). Pride and Prejudice? Structural Evidence of Social Pressure from a Natural Field Experiment with Committees.

Gourieroux, C., Monfort, A., and Renault, E. (1993). Indirect Inference. *Journal of Applied Econometrics*, 8(Supplement: Special Issue on Econometric Inference Using Simulation Techniques):S85–S118.

Green, D. A. and Worswick, C. (2012). Immigrant earnings profiles in the presence of human capital investment: Measuring cohort and macro effects. *Labour Economics*, 19(2):241–259.

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

Imai, S. and Keane, M. (2004). Intertemporal Labor Supply and Human Capital Accumulation. *International Economic Review*, 45(2):601–641.

Imbert, C. and Papp, J. (2015). Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee. *American Economic Journal: Applied Economics*, 7(2):233–263.

Imbert, C. and Papp, J. (forthcoming). Short-term Migration, Rural Public Works and Urban Labor Markets: Evidence from India. *Journal of the European Economic Association*.

Kennan, J. and Walker, J. (2011). The Effect of Expected Income on Individual Migration Decisions. *Econometrica*, 79(1):211–251.

Kırdar, M. (2012). Estimating the Impact of Immigrants on the Host Country Social Security System when Return Migration is an Endogenous Choice. *International Economic Review*, 53(2):453–486.

Kleemans, M. (2015). Migration Choice under Risk and Liquidity Constraints.

Lacuesta, A. (2010). A Revision of the Self-selection of Migrants Using Returning Migrant's Earnings. *Annals of Economics and Statistics*, (97/98):235–259.

Laszlo, S. and Santor, E. (2009). Migration, Social Networks, and Credit: Empirical Evidence from Peru. *The Developing Economies*, 47(4):383–409.

Lessem, R. (2018). Mexico–U.S. Immigration: Effects of Wages and Border Enforcement. *Review of Economic Studies*, 85(4):2353–2388.

Lessem, R. and Nakajima, K. (2019). Immigrant Wages and Recessions: Evidence from Undocumented Mexicans. *European Economic Review*, 114.

Lise, J., Seitz, S., and Smith, J. (2004). Equilibrium Policy Experiments and the Evaluation of Social Programs. *NBER Working Paper*, 10283.

Llull, J. (2018). Selective Immigration Policies and the U.S. Labor Market.

Llull, J. and Miller, R. (2018). Internal Migration and Work Experience in Dual Labor Markets.

Lubotsky, D. (2007). Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings. *Journal of Political Economy*, 115(5):820–867.

Majlesi, K. and Narciso, G. (2018). International import competition and the decision to migrate: Evidence from Mexico. *Journal of Development Economics*, 132:75–87.

McKenzie, D. and Rapoport, H. (2007). Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico. *Journal of Development Economics*, 84(1):1–24.

McKenzie, D. and Rapoport, H. (2010). Self-Selection Patterns in Mexico-US Migration: The Role of Migration Networks. *Review of Economics and Statistics*, 92(4):811–821.

Meghir, C., Mobarak, M., Mommaerts, C., and Morten, M. (2015). Migration and Consumption Insurance in Bangladesh.

Mendola, M. (2018). Global evidence on prospective migrants from developing countries. *Mimeo*.

Morten, M. (2019). Temporary Migration and Endogenous Risk Sharing in Village India. *Journal of Political Economy*, 127(1):1–46.

Munshi, K. and Rosenzweig, M. (2016). Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap. *American Economic Review*, 106(1):46–98.

Nakajima, K. (2015). The Fiscal Impact of Border Tightening. Job Market Paper, University of Wisconsin-Madison.

OECD (2007). *Pensions at a Glance 2007: Public Policies across OECD Countries*. OECD Publishing, Paris.

Orrenius, P. and Zavodny, M. (2005). Self-selection among undocumented immigrants from Mexico. *Journal of Development Economics*, 78(1):215–240.

Oswald, F. (forthcoming). The Effect of Homeownership on the Option Value of Regional Migration. *Quantitative Economics*.

Piyapromdee, S. (2017). The Impact of Immigration on Wages, Internal Migration and Welfare.

Public Law 109-367-Oct. 26 (2006). Secure Fence Act.

Reinhold, S. and Thom, K. (2013). Migration Experience and Earnings in the Mexican Llabor Market. *Journal of Human Resources*, 48(3):768–820.

Rendon, S. and Cuecuecha, A. (2010). International Job Search: Mexicans in and out of the US. *Review of Economics of the Household*, 8(1):53–82.

Rosenzweig, M. and Udry, C. (2019). Assessing the Benefits of Long-run Weather Forecasting for the Rural Poor: Farmer Investments and Worker Migration in a Dynamic Equilibrium Model. *NBER Working Paper*, 25894.

Singleton, K. (2006). *Empirical Dynamic Asset Pricing: Model Specification and Econometric Assessment*. Princeton University Press.

Thom, K. (2010). Repeated Circular Migration: Theory and Evidence from Undocumented Migrants. *Mimeo, New York University*.

Todd, P. and Wolpin, K. (2006). Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility. *American Economic Review*, 96(5):1384–1417.

World Bank (2015). World Development Indicators. Washington, D.C.

APPENDIX (For Online Publication)

A Progresa Evaluation Data

In May 1998, the Mexican Programa de Educación, Salud, y Alimenación (Progresa, later called Oportunidades, now Prospera) started handing out conditional cash transfers in a randomized group of 320 "treated" communities. Eligible families in program communities received cash transfers for each child aged 8 to 21 who attended school in one of the last four grades of primary, or the first three grades of secondary school. To evaluate the program, household data in both this treatment group and in a control group of 186 communities were collected.[38] Eligibility of families was determined by a pre-program survey in 1997, based on a multi-dimensional marginalization measure, detailed in Skoufias, E., Davis, B., and Behrman, J. (1999, An Evaluation of the Selection of Beneficiary Households in the Education, Health, and Nutrition Program (Progresa) of Mexico. Inter-national Food Policy Research Institute, Washington, DC).

Prior to the introduction of Progresa, a pre-program survey was conducted in 1997. This pre-program sample allows for a comparison of prior outcomes of households in treatment and control localities. Information on loan take-up is not available for 1997. Instead, Table 5 lists differences between a number of wealth proxies and other household characteristics. Overall, this comparison suggests small and statistically insignificant differences in these dimensions. See also Behrman, J. R. and Todd, P. E. (1999, Randomness in the Experimental Samples of Progresa (Education, Health, and Nutrition Program). International Food Policy Research Institute, Washington, DC) for an extensive evaluation of the Progresa randomization.

[38] Programa de Educacióon, Salud, y Alimenación (2012, Mexico, Evaluation of Progresa. http://hdl.handle.net/1902.1/18235. Harvard Dataverse, V1. Accessed: 31.03.2015.)

Table 5: Comparison of pre-treatment household wealth proxies in program and control communities.

	Control mean	Difference between treatment and control
age of HH head	40.320	−0.164
		(0.220)
literate HH head	0.744	−0.007
		(.011)
HH head works	0.947	−0.010
		(0.006)
hours worked	42.134	+0.261
		(0.395)
hourly wage (in pesos)	3.450	−0.081
		(0.069)
number of household members	6.99	+0.021
		(0.052)
number of rooms	1.640	−0.003
		(0.024)
land owned (in hectares)	1.902	−0.054
		(0.099)
Observations	2450	6596

Progresa evaluation data, 1997. Column 1 lists mean outcomes for the control sample, while column 2 shows the difference between program and control observations before introduction of the program, with standard errors in parentheses.

B Model Specification

This appendix details the specification of components of the model presented in Section 3.

Transition probabilities. The probability of gaining dependent family is specified as

$$p_{f+}(\Omega_{it}|f_{it-1} = 0) = \Phi\left(\psi_0^{f+} + g^{f+}(a_{it})\right),$$

where $\Phi()$ denotes the standard normal cumulative distribution function. $g^{f+}(a_{it})$ is a piecewise linear function of age with nodes at 30 and 50 years, and slopes $\psi^{f+}_{a\leq 30}, \psi^{f+}_{30<a\leq 50}$ and $\psi^{f+}_{a>50}$. Similarly, the probability of losing dependent family is given by another transformed piecewise linear function of age,

$$p_{f-}(\Omega_{it}|f_{it-1} = 1) = \Phi\left(\psi_0^{f-} + g^{f-}(a_{it})\right),$$

where $g^{f-}(a_{it})$ again has nodes at 30 and 50 years, and slopes $\psi^{f-}_{a\leq 30}, \psi^{f-}_{30<a\leq 50}$ and $\psi^{f-}_{a>50}$. The probabilities of obtaining or losing a legal permit to work in the U.S. are given by

$$p_{d+}(\Omega_{it}|d_{it-1} = 0) = \Phi\left(\psi_0^{d+} + g^{d+}(a_{it}) + \psi_e^{d+}\mathbb{1}[e_{it} = w]\right)$$

and

$$p_{d-}(\Omega_{it}|d_{it-1} = 1) = \Phi\left(\psi_0^{d-} + g^{d-}(a_{it}) + \psi_e^{d-}\mathbb{1}[e_{it} = w]\right),$$

respectively, where again $g^{d+}(a_{it})$ and $g^{d-}(a_{it})$ are piecewise linear functions with nodes at 30 and 50 years of age, and correspondingly denoted slope parameters.

Finally, when an individual is in Mexico, jobs are found and lost with probabilities

$$\begin{aligned}\lambda_w(\Omega_{it}|e_{it-1} = nw, l_{it} = MX) \;&=\; \Phi\Big(\psi_0^{w,MX} + g^{w,MX}(a_{it}) + \psi_X^{w,MX}\mathbb{1}[X_{it}^{US} > 0] \\ &\qquad + \psi_s^{w,MX}\mathbb{1}[s_t = summer]\Big)\end{aligned}$$

and

$$\begin{aligned}\lambda_{nw}(\Omega_{it}|e_{it-1} = w, l_{it} = MX) \;&=\; \Phi\Big(\psi_0^{nw,MX} + g^{nw,MX}(a_{it}) + \psi_X^{nw,MX}\mathbb{1}[X_{it}^{US} > 0] \\ &\qquad + \psi_s^{nw,MX}\mathbb{1}[s_t = summer]\Big),\end{aligned}$$

and when having migrated to the U.S. with probabilities

$$\lambda_w(\Omega_{it}|e_{it-1} = nw, l_{it} = US) = \Phi\Big(\psi_0^{w,US} + g^{w,US}(a_{it}) + \psi_X^{w,US} X_{it} + \psi_s^{w,US} \mathbb{1}[s_t = summer] + \psi_d^{w,US} d_{it}\Big)$$

and

$$\lambda_{nw}(\Omega_{it}|e_{it-1} = w, l_{it} = US) = \Phi\Big(\psi_0^{nw,US} + g^{nw,US}(a_{it}) + \psi_X^{nw,US} X_{it} + \psi_s^{nw,US} \mathbb{1}[s_t = summer] + \psi_d^{nw,US} d_{it}\Big),$$

with linear splines $g^{w,MX}(a_{it}), g^{w,MX}(a_{it}), g^{w,US}(a_{it})$ and $g^{w,US}(a_{it})$ that all have nodes at 25, 40 and 55 years of age, and correspondingly denoted slope parameters.

Earnings functions. Log biannual earnings are given

$$\log y(\Omega_{it}) = \alpha_i^l + f^l(a_{it}, X_{it}^{US}) + v_{it}^l,$$

with the location specific function relating age and U.S. experience to earnings

$$f^l(a_{it}, X_{it}^{US}) = g_a^{y,l}(a_{it}) + \mathbb{1}[l_{it} = US] g_X^y(X_{it}^{US}),$$

where the piecewise linear functions $g_a^{y,MX}(a_{it})$ and $g_a^{y,US}(a_{it})$ have nodes at 20, 25, 35 and 50 years of age, and $g_X^{y,US}(X_{it}^{US})$ has nodes at 5 and 10 years of U.S. experience. Idiosyncratic shocks to log earnings, v_{it}^l, are normally distributed and independent across time and individuals, with mean zero and location specific variance $\sigma^2_{v^l}$.

Retirement benefits. Individuals are assumed to live until age $a^{end} = 75$, which corresponds to the life expectancy in Mexico at the middle of my sample period in 2002 (World Bank, 2015). Retirement schemes in Mexico and in the U.S. are approximated based on OECD (2007) data as follows: individuals retire at age $a^{ret} = 65$, with benefits $y^{ret}(\Omega_{it})$ corresponding to a net replacement rate in Mexico of 37.9 percent (55.3 percent in the U.S.) of potential earnings at age 64. If a migrant retires in the U.S., the retirement benefits are a weighted average between Mexican entitlements and benefits from the U.S., with the weight toward U.S. benefits being the fraction of working life spent there, $X^{US}/(65-16)$.

Borrowing limit. Households with a working age head can take up credit. They face two constraints to the maximum amount of debt, $B(\mathrm{E}[y_{it}^{MX}], \Omega_{it})$, they can hold: The first constraint depends on retirement benefits (used as collateral), and becomes tighter as agents get older, ensuring full debt repayment. This limit typically however is too generous to match the debt level observed in the data. I thus estimate a second—potentially tighter—constraint that still captures better access to credit by high-income households, and which is a linear function of expected earnings, so that for $a_{it} < a^{ret}$,

$$B(\mathrm{E}[y_{it}], \Omega_{it}) = \min\left\{\delta_0 + \delta_y \mathrm{E}[y_{it}]\ ,\ y^{ret}(\Omega_{it})\left(\frac{(1+r)^{a^{end}-a^{ret}}-1}{r(1+r)^{a^{end}-a_{it}}}\right)\right\}.$$

Interest rates and time preference. The biannual real interest rate is set to $r = 0.02$, based on the World Bank's (2015) World Development Indicators. The biannual discount factor β is set to $1/(1+r)$.

Preference shocks. Transitory preference shocks $\varepsilon_{it}^{\mathbf{l}}$ are extreme value distributed with cumulative distribution function $P(\varepsilon \leq x) = \exp(-\exp(-x/\sigma^{\varepsilon}(a_{it})))$. The spread parameter $\sigma^{\varepsilon}(a_{it})$ is specified as a linear function of age,

$$\sigma^{\varepsilon}(a_{it}) = \sigma_0^{\varepsilon} + \sigma_a^{\varepsilon} age_{it},$$

where the parameters σ_0^{ε} and σ_a^{ε} are estimated within the model.

Monetary cost of migration. Migration costs are a function of age, legal status, whether a household member has been to the U.S. previously, and of whether it is the household head or family that migrates. The age specific part $g_C(age_{it})$ is a piecewise linear function, with nodes at 30 and 50 years of age and slopes $\gamma_{a\leq 30}$, $\gamma_{30<a\leq 50}$ and $\gamma_{a>50}$, so that the overall cost is given by

$$\begin{aligned} C(\Omega_{it}) &= \gamma_0 + g_C(age_{it}) + \gamma_{undoc} d_{it} + \gamma_X \mathbb{1}[X_{it}^{US} > 0] \\ C^f(\Omega_{it}) &= C(\Omega_{it}) + \gamma_f. \end{aligned}$$

Apprehension probability. Due to apprehensions of undocumented migrants, attempted migrations from Mexico to the U.S. fail with probability

$$p_a(\Omega_{it}|l_{it-1} = MX) = \psi^a(1 - d_{it}).$$

Annual apprehension probabilities at the border are reported by the Mexican Migration Project. I use this information directly, and set $\psi^a = 0.2246$. Migrants in the U.S. can always return to Mexico, hence $p_a(\Omega_{it}|l_{it-1} = US) = 0$.

C Assumptions on Debt Limits and the Bias in Estimates of Migration Costs

The empirical relevance of assumptions regarding migrants' access to credit is revealed by examining the criterion function minimized by the indirect inference estimator, which takes as argument the vector of parameters. If a restricted model with $B = 0$ indeed produces biased estimates, the criterion function would—for one or several of the estimated parameters—attain its minimum at different values than the unrestricted model. I illustrate this for the intercept parameter γ_0 of the migration cost function.[39] Figure 11 depicts the estimation criterion against different values of this parameter, separately under the unrestricted (solid line) and the restricted model (dashed line). While under the unrestricted model the criterion is minimized at 5,757 USD, the criterion under the restricted model attains its minimum at an about 3,700 USD lower value. Part of this strong bias may dissipate to multiple smaller biases in other parameters. Nonetheless, this exercise suggests that a model which does not take into account that part of the cost of migration can be paid on credit may be severely misspecified, and underestimate migration costs.

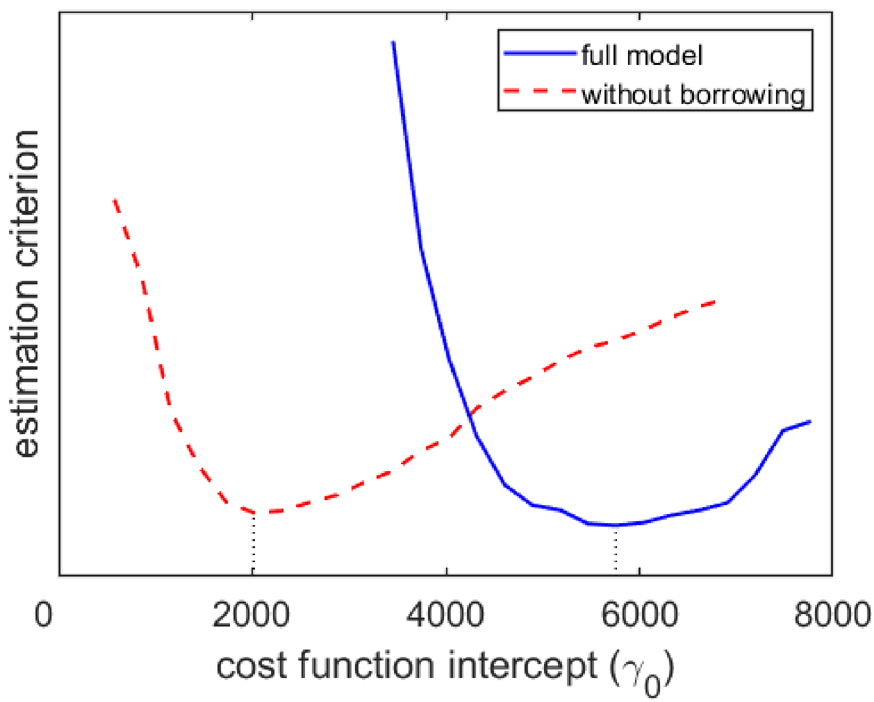


Figure 11: Estimation bias in the absence of borrowing. The figure plots the moment criterion minimized by the indirect inference estimator against different values for the intercept parameter γ_0 of the migration cost function $C(\Omega)$, separately for the full model of Section 3 (solid line), and for a restricted model that rules out borrowing by assuming $B = 0$ (dashed line). The criterion is computed for a simulated sample of 40,000 agents.

[39] The monetary cost of migration for household heads is specified as $C(\Omega_{it}) = \gamma_0 + g_C(age_{it}) + \gamma_{undoc}(1 - d_{it}) + \gamma_X \mathbb{1}[X_{it}^{US} > 0]$, see Section 3 and Appendix B.

D Asymptotic Distribution of the Simulated Minimum Distance Estimator with Multiple Samples

This appendix derives the asymptotic distribution of the estimator used in this paper. The derivation extends results by Gourieroux et al. (1993) for the indirect inference estimator to a case where identification requires moments from multiple data sets.[40] The following assumptions need to be made:

Assumption 1. The different samples used are drawn independently. This implies that any cross-sample moments are zero and most plausible weighting matrices W, including the efficient one, will be block diagonal, with a block W_ς for each set of moments derived from the same sample ς.

Assumption 2. The criterion function

$$\Gamma(\vartheta) = D(\vartheta)'WD(\vartheta) = \left(m^d - m^s(\vartheta)\right)' W \left(m^d - m^s(\vartheta)\right)$$

to be minimized, is differentiable and attains its global minimum at the true parameter vector θ.

Assumption 3. $\frac{\partial D}{\partial \vartheta'}\Big|_\theta$ has full rank, which ensures identification of parameters θ through the moments in $D(\vartheta)$.

Assumption 4. The moments targeted, m^d, are aymptotically normally distributed.

Assumption 5. Sample sizes N_ς of the data sets used increase at a rate

$$\lim_{\substack{N_\varsigma \to \infty \\ N \to \infty}} (N_\varsigma / N) = n_\varsigma,$$

with $0 < n_\varsigma < \infty$, and where $N = \sum_\varsigma N_\varsigma$. This ensures that none of the samples is irrelevant relative to the others.

Assumption 6. Simulated sample sizes N_ς^s increase at a rate such that

$$\lim_{\substack{N_\varsigma \to \infty \\ N_\varsigma^s \to \infty}} (N_\varsigma / N_\varsigma^s) = n_\varsigma^s,$$

with $0 < n_\varsigma^s < \infty$.

Then, by the first order conditions for a minimum of the criterion function at the parameter estimate $\hat{\theta}$,

$$\frac{\partial \Gamma}{\partial \vartheta}\bigg|_{\hat{\theta}} = -2\,\frac{\partial m^{s\prime}}{\partial \vartheta}\bigg|_{\hat{\theta}} W \left(m^d - m^s(\hat{\theta})\right) = 0, \quad \text{or} \quad \frac{\partial D'}{\partial \vartheta}\bigg|_{\hat{\theta}} W D(\hat{\theta}) = 0.$$

[40] The derivation builds on Angrist and Krueger (1992) and Arellano and Meghir (1992), who derive properties of the two sample IV estimator. Also related is the discussion by Singleton (2006) of GMM estimation with time series data of unequal length.

By the mean value theorem, for some $\bar{\theta}$ between $\hat{\theta}$ and θ,

$$D(\hat{\theta}) = D(\theta) + \left.\frac{\partial D}{\partial \vartheta'}\right|_{\bar{\theta}} (\hat{\theta} - \theta).$$

Substituting into the first order condition yields

$$\hat{\theta} - \theta = -\left(\left.\frac{\partial D'}{\partial \vartheta}\right|_{\hat{\theta}} W \left.\frac{\partial D}{\partial \vartheta'}\right|_{\bar{\theta}} \right)^{-1} \left.\frac{\partial D'}{\partial \vartheta}\right|_{\hat{\theta}} W D(\theta).$$

If the observed moment vector m^d consists of moments from several independently drawn samples ς, and W is block diagonal as described above, $\Gamma(\vartheta)$ can be written as a sum of the contributions to the criterion by the moments of each sample. The first order conditions thus become,

$$0 = \left.\frac{\partial D'}{\partial \vartheta}\right|_{\hat{\theta}} W \left(m^d - m^s(\hat{\theta}) \right) = \sum_{\varsigma} \left.\frac{\partial D'_{\varsigma}}{\partial \vartheta}\right|_{\hat{\theta}} W_{\varsigma} \left(m^d_{\varsigma} - m^s_{\varsigma}(\hat{\theta}) \right),$$

where m^d_{ς} and m^s_{ς} are vectors of observed and simulated moments from sample ς. Under assumption 6, the variance of simulated moments $m^s_{\varsigma}(\theta)$ decreases at a rate n^s_{ς} relative to the variance of the empirical moments m^d_{ς}. Thus, under assumptions 4-6, the asymptotic distribution for $\hat{\theta}$ is given by

$$\begin{aligned} \sqrt{N}(\hat{\theta} - \theta) \xrightarrow{d} \mathcal{N}\Bigg(0, & \left(\left.\frac{\partial D'}{\partial \vartheta}\right|_{\hat{\theta}} W \left.\frac{\partial D}{\partial \vartheta'}\right|_{\hat{\theta}} \right)^{-1} \\ & \cdot \left(\sum_{\varsigma} N(1 + n^s_{\varsigma}) \left.\frac{\partial D'_{\varsigma}}{\partial \vartheta}\right|_{\hat{\theta}} W_{\varsigma} \mathrm{var}\left(m^d_{\varsigma} \right) W'_{\varsigma} \left.\frac{\partial D_{\varsigma}}{\partial \vartheta'}\right|_{\hat{\theta}} \right) \\ & \cdot \left(\left.\frac{\partial D'}{\partial \vartheta}\right|_{\hat{\theta}} W \left.\frac{\partial D}{\partial \vartheta'}\right|_{\hat{\theta}} \right)^{-1} \Bigg). \end{aligned}$$

E Moments Used for Identification

Identification and model fit are discussed in Sections 4.1 and 5.1, respectively. This appendix provides further details. Under the model, all parameters are identified jointly from the vector of moments used for estimation. To provide a better intuition, however, Table 6 lists the model parameters to be estimated and the identifying moments more systematically.

Parameters	Identifying moments	Data set
$p_{f+}(\Omega), p_{f-}(\Omega)$	transitions to and from having dependent family by age	MxFLS
$p_{d+}(\Omega), p_{d-}(\Omega)$	transitions to and from having a U.S. visa by age and employment status	MMP
$\lambda_w(\Omega), \lambda_{nw}(\Omega)$	fraction working, season last worked, and transitions into and out of employment by location, age, legal status, having been to the U.S. and season	MMP, MxFLS, SIPP
$f^l(a, X^{US})$	log earnings by location, age and U.S. experience	MxFLS, SIPP
σ_u^l	standard deviation of log earnings residuals by location	MxFLS, SIPP
ϕ_c	changes in assets and debt by age	MxFLS
$\phi_f^{\mathbf{l}}$	family location by age, and stock of assets/debt by family status	MxFLS, MMP
$\tilde{\alpha}_A$	asset level	MxFLS
$\sigma^\varepsilon(a)$	number of U.S. migrations by age	MMP
$C(\Omega)$	fraction migrating to the U.S. by age, previous migration, family and legal status, and by stock of assets	MMP, MxFLS
$B(\mathrm{E}[y^{MX}], \Omega_{it})$	debt level by age, and effect of randomized cash transfer on loan amount taken within the past six months	MxFLS, Progresa
pdf of α_τ^l, π_τ	log earnings by location, and deciles of within-individual mean log earnings residuals by location;	MxFLS, SIPP
	deciles of last migration duration net of age;	MxFLS
	deciles of duration of current trip net of age;	SIPP
	log earnings in Mexico by deciles of within-individual mean residual of last trip duration net of age;	MxFLS
	log earnings in the U.S. by deciles of within-individual mean residual of current trip duration net of age	SIPP
$\{\omega_\tau^{MMP}\}_{\tau=1}^T$	fraction residing in the U.S. by age, and deciles of within-individual mean residual from regression of location on age	MMP
$\{\omega_\tau^{Progresa}\}_{\tau=1}^T$	deciles of log earnings in Mexico	Progresa

Table 6: Identification of model parameters

To analyze the mapping of parameters into the moments used in the estimation, I numerically compute the gradient matrix of the moment vector with respect to the parameter vector. A necessary condition for identification is that for each parameter there are one or more moments with a non-zero gradient, and that there is no collinearity between gradient vectors for different parameters. Figure 12 illustrates this gradient matrix graphically. Darker shades indicate a larger response of a predicted moment to a change in a particular parameter. As there are no rows that are white throughout, there exists at least one identifying moment for each parameter, and in fact all parameters are identified by more than one moment.

Section 4.1 explains that including in the structural estimation the non-parametric estimate of the treatment effect of the randomized income provided by Progresa cash transfers on borrowing identifies the effect of earnings on credit, δ_y, in the model. To show that this is the case, Figure 13 plots the contribution of this moment to the estimation criterion. Specifically, it traces the squared difference between the observed treatment effect of Progresa on borrowing and its simulated model counterpart for different values of the structural parameter δ_y. The graph shows that the model indeed matches the data only when δ_y is at its estimated value of 2.6. Tables 7-14 list the full set of empirical moments used in the estimation together with their simulated counterparts and standard deviations.

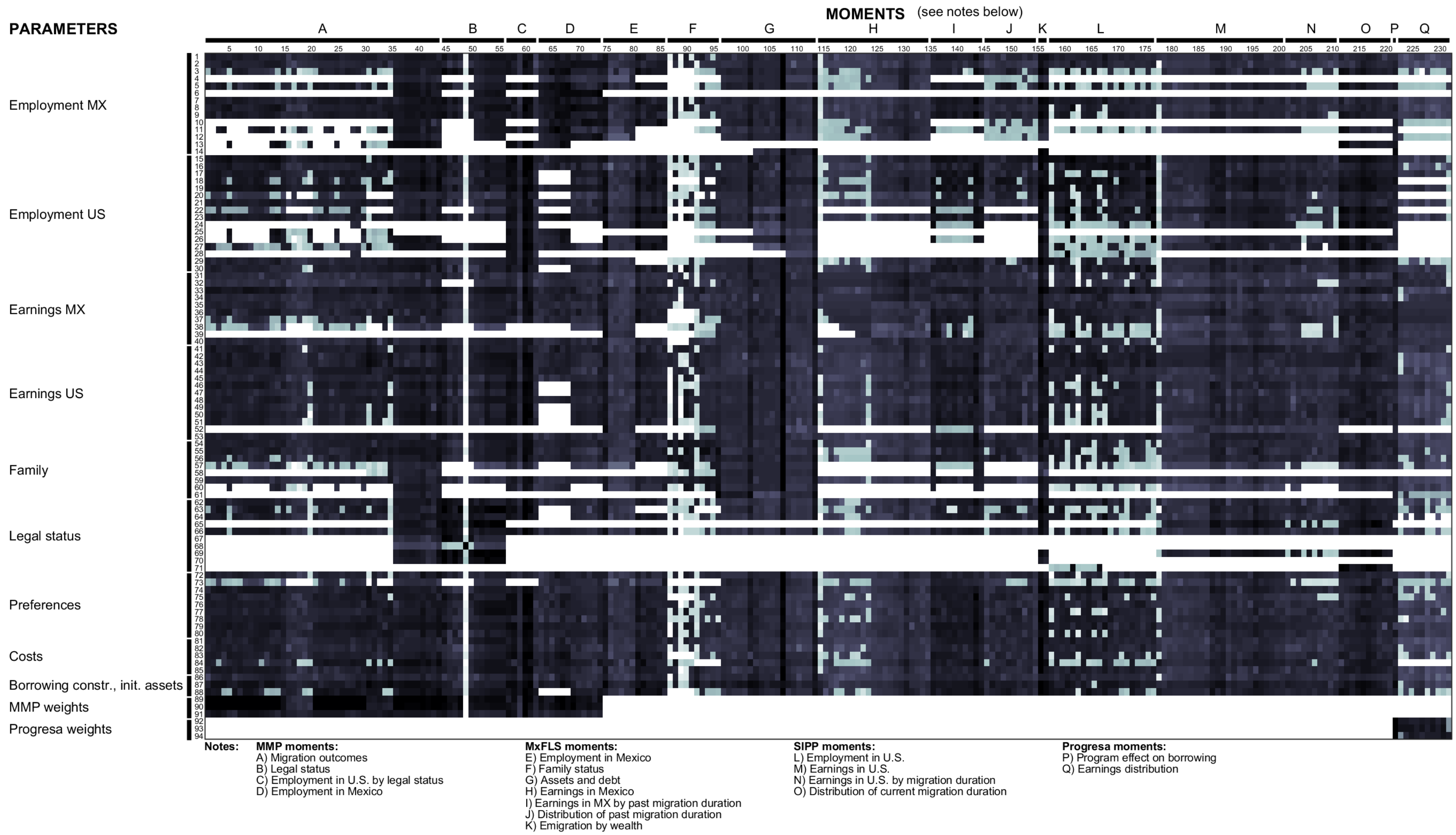


Figure 12: Mapping of moments into parameters. The figure illustrates the gradient matrix of moments used for identification with respect to model parameters. Darker shades indicate a stronger sensitivity of moments to changes in parameters. Moments are computed for a simulated sample of 40,000 agents.

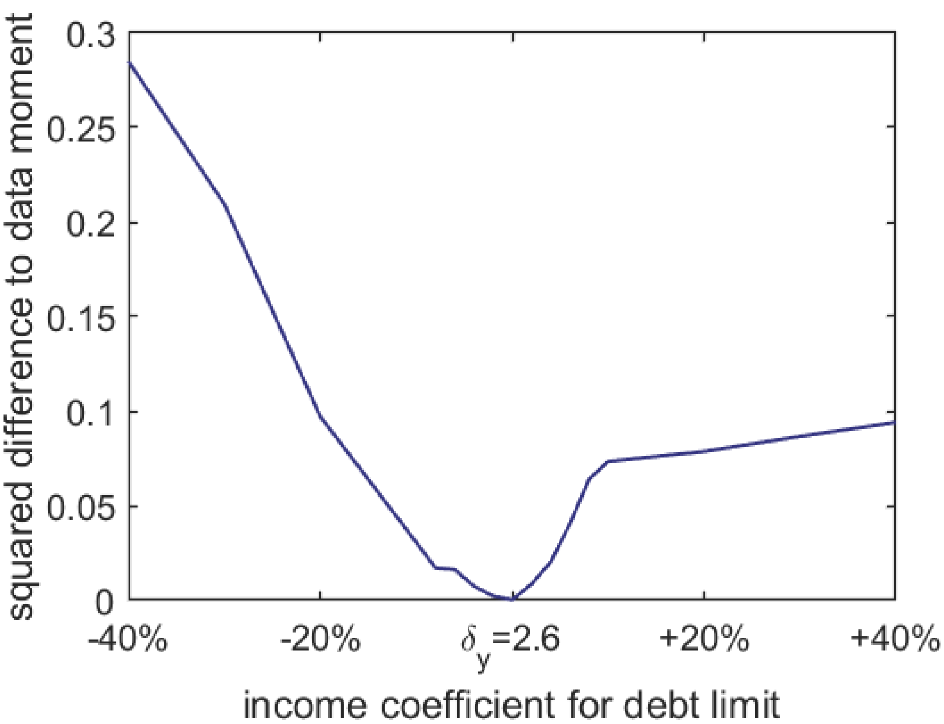


Figure 13: Credit access and the ATE of Progresa. The figure plots the contribution of the estimated treatment effect of Progresa on borrowing to the estimation criterion minimized by the indirect inference estimator against different values for the structural effect δ_y of income on the debt limit. Specifically, it shows the squared difference between the observed simulated moment for different values δ_y. The simulated moment is computed for a simulated sample of 40,000 agents.

Table 7: Family and legal status transitions.

Moment	Data	Standard error	Simulation
Transition to having family (MxFLS):			
$\mathbb{1}[16 \leq age < 25]$	0.429	(0.179)	0.497
$\mathbb{1}[25 \leq age < 35]$	0.553	(0.077)	0.627
$\mathbb{1}[35 \leq age < 45]$	0.372	(0.072)	0.385
$\mathbb{1}[45 \leq age < 55]$	0.269	(0.066)	0.102
$\mathbb{1}[55 \leq age < 65]$	0.283	(0.061)	0.297
Transition to not having family (MxFLS):			
$\mathbb{1}[16 \leq age < 25]$	0.053	(0.024)	0.072
$\mathbb{1}[25 \leq age < 35]$	0.007	(0.005)	0.006
$\mathbb{1}[35 \leq age < 45]$	0.013	(0.004)	0.008
$\mathbb{1}[45 \leq age < 55]$	0.026	(0.004)	0.031
$\mathbb{1}[55 \leq age < 65]$	0.043	(0.005)	0.036
Regression of transition to having a U.S. visa (MMP) on:			
$\mathbb{1}[16 \leq age < 25]$	0.012	(0.024)	0.021
$\mathbb{1}[25 \leq age < 35]$	0.284	(0.022)	0.312
$\mathbb{1}[35 \leq age < 45]$	0.433	(0.023)	0.609
$\mathbb{1}[45 \leq age < 55]$	0.526	(0.023)	0.468
$\mathbb{1}[55 \leq age < 65]$	0.514	(0.024)	0.500
$\mathbb{1}[working]$	0.369	(0.022)	0.260
Regression of transition to not having a U.S. visa (MMP) on:			
$\mathbb{1}[16 \leq age < 25]$	0.020	(0.012)	0.012
$\mathbb{1}[25 \leq age < 35]$	0.015	(0.010)	0.007
$\mathbb{1}[35 \leq age < 45]$	0.009	(0.010)	0.003
$\mathbb{1}[45 \leq age < 55]$	0.002	(0.010)	0.002
$\mathbb{1}[55 \leq age < 65]$	0.002	(0.014)	0.002
$\mathbb{1}[working]$	-0.002	(0.009)	-0.002

Data moments obtained from the MMP and the MxFLS as indicated. Simulation based on 40,000 agents $\times$ 50 years $\times$ 2 seasons.

Table 8: Employment in Mexico.

Moment	Data	Standard error	Simulation
Regression of transition into work in Mexico on:			
$\mathbb{1}[16 \leq age < 25]$	0.459	(0.016)	0.770
$\mathbb{1}[25 \leq age < 35]$	0.329	(0.047)	0.475
$\mathbb{1}[35 \leq age < 45]$	0.095	(0.039)	0.140
$\mathbb{1}[45 \leq age < 55]$	0.024	(0.031)	0.024
$\mathbb{1}[55 \leq age < 65]$	0.033	(0.025)	0.013
$\mathbb{1}[been\ in\ U.S.]$	−0.002	(0.043)	−0.042
Regression of transition out of work in Mexico on:			
$\mathbb{1}[16 \leq age < 25]$	0.001	(0.000)	0.000
$\mathbb{1}[25 \leq age < 35]$	0.001	(0.000)	0.001
$\mathbb{1}[35 \leq age < 45]$	0.001	(0.000)	0.002
$\mathbb{1}[45 \leq age < 55]$	0.002	(0.000)	0.003
$\mathbb{1}[55 \leq age < 65]$	0.004	(0.000)	0.005
$\mathbb{1}[been\ in\ U.S.]$	−0.000	(0.000)	−0.001
Regression of working in Mexico on:			
$\mathbb{1}[16 \leq age < 25]$	0.946	(0.020)	0.968
$\mathbb{1}[25 \leq age < 35]$	0.956	(0.015)	0.973
$\mathbb{1}[35 \leq age < 45]$	0.948	(0.015)	0.982
$\mathbb{1}[45 \leq age < 55]$	0.898	(0.015)	0.973
$\mathbb{1}[55 \leq age < 65]$	0.770	(0.016)	0.927
$\mathbb{1}[summer]$	−0.018	(0.014)	−0.001
Regression of season last worked in Mexico on:			
$\mathbb{1}[16 \leq age < 25]$	0.689	(0.208)	0.558
$\mathbb{1}[25 \leq age < 35]$	0.660	(0.195)	0.573
$\mathbb{1}[35 \leq age < 45]$	0.770	(0.207)	0.613
$\mathbb{1}[45 \leq age < 55]$	0.882	(0.190)	0.585
$\mathbb{1}[55 \leq age < 65]$	0.769	(0.190)	0.686
$\mathbb{1}[summer]$	−0.637	(0.185)	−0.063

Data moments obtained from the MxFLS. Simulation based on 40,000 agents × 50 years × 2 seasons.

Table 9: Employment in the U.S.

Moment	Data	Standard error	Simulation
Regression of transition into work in the U.S. (SIPP) on:			
$\mathbb{1}[16 \leq age < 25 \cap winter]$	0.500	(0.115)	0.642
$\mathbb{1}[25 \leq age < 35 \cap winter]$	0.500	(0.048)	0.447
$\mathbb{1}[35 \leq age < 45 \cap winter]$	0.308	(0.052)	0.211
$\mathbb{1}[45 \leq age < 55 \cap winter]$	0.145	(0.044)	0.068
$\mathbb{1}[55 \leq age < 65 \cap winter]$	0.034	(0.035)	0.006
$\mathbb{1}[16 \leq age < 25 \cap summer]$	0.000	(0.145)	0.512
$\mathbb{1}[25 \leq age < 35 \cap summer]$	0.157	(0.046)	0.285
$\mathbb{1}[35 \leq age < 45 \cap summer]$	0.152	(0.048)	0.117
$\mathbb{1}[45 \leq age < 55 \cap summer]$	0.075	(0.036)	0.022
$\mathbb{1}[55 \leq age < 65 \cap summer]$	0.052	(0.030)	0.004
Regression of transition out of work in the U.S. (SIPP) on:			
$\mathbb{1}[16 \leq age < 25 \cap winter]$	0.023	(0.013)	0.012
$\mathbb{1}[25 \leq age < 35 \cap winter]$	0.023	(0.004)	0.018
$\mathbb{1}[35 \leq age < 45 \cap winter]$	0.023	(0.004)	0.015
$\mathbb{1}[45 \leq age < 55 \cap winter]$	0.022	(0.005)	0.018
$\mathbb{1}[55 \leq age < 65 \cap winter]$	0.085	(0.008)	0.081
$\mathbb{1}[16 \leq age < 25 \cap summer]$	0.005	(0.009)	0.003
$\mathbb{1}[25 \leq age < 35 \cap summer]$	0.004	(0.003)	0.002
$\mathbb{1}[35 \leq age < 45 \cap summer]$	0.004	(0.003)	0.002
$\mathbb{1}[45 \leq age < 55 \cap summer]$	0.008	(0.004)	0.003
$\mathbb{1}[55 \leq age < 65 \cap summer]$	0.009	(0.008)	0.019
Regression of working in the U.S. (MMP) on:			
$\mathbb{1}[legal]$	−0.003	(0.013)	−0.040
U.S. experience	0.001	(0.001)	−0.005
constant	0.886	(0.007)	0.888
Regression of fraction of year worked in the U.S. (MMP) on:			
$\mathbb{1}[legal]$	−0.186	(0.010)	0.005
U.S. experience	0.011	(0.001)	0.001
constant	0.855	(0.006)	0.743

Data moments obtained from the MMP and the SIPP as indicated. Simulation based on 40,000 agents × 50 years × 2 seasons.

Table 10: Earnings.

Moment	Data	Standard error	Simulation
Regression of log annual earnings in Mexico (MxFLS) on:			
$\mathbb{1}[16 \leq age \leq 20]$	7.885	(0.090)	8.249
$\mathbb{1}[20 < age \leq 25]$	8.307	(0.043)	8.438
$\mathbb{1}[25 < age \leq 30]$	8.333	(0.031)	8.568
$\mathbb{1}[30 < age \leq 35]$	8.347	(0.028)	8.687
$\mathbb{1}[35 < age \leq 40]$	8.340	(0.027)	8.759
$\mathbb{1}[40 < age \leq 45]$	8.317	(0.028)	8.802
$\mathbb{1}[45 < age \leq 50]$	8.226	(0.030)	8.848
$\mathbb{1}[50 < age \leq 55]$	8.120	(0.033)	8.885
$\mathbb{1}[55 < age \leq 60]$	8.026	(0.038)	8.900
$\mathbb{1}[60 < age < 65]$	7.901	(0.051)	8.892
standard deviation of residual	0.946	(0.016)	0.758
Regression of log annual earnings in the U.S. (SIPP) on:			
$\mathbb{1}[16 \leq age \leq 20]$	8.915	(0.116)	8.777
$\mathbb{1}[20 < age \leq 25]$	9.418	(0.049)	8.912
$\mathbb{1}[25 < age \leq 30]$	9.457	(0.045)	9.090
$\mathbb{1}[30 < age \leq 35]$	9.547	(0.045)	9.251
$\mathbb{1}[35 < age \leq 40]$	9.468	(0.047)	9.360
$\mathbb{1}[40 < age \leq 45]$	9.490	(0.049)	9.426
$\mathbb{1}[45 < age \leq 50]$	9.554	(0.054)	9.520
$\mathbb{1}[50 < age \leq 55]$	9.398	(0.060)	9.577
$\mathbb{1}[55 < age \leq 60]$	9.270	(0.071)	9.628
$\mathbb{1}[60 < age < 65]$	8.914	(0.114)	9.523
$\mathbb{1}[5 \leq U.S.\ experience < 10]$	0.181	(0.046)	0.260
$\mathbb{1}[10 \leq U.S.\ experience < 15]$	0.304	(0.047)	0.300
$\mathbb{1}[15 \leq U.S.\ experience]$	0.477	(0.043)	0.354
standard deviation of residual	0.703	(0.014)	0.892

Data moments obtained from the MxFLS and the SIPP as indicated. Simulation based on 40,000 agents $\times$ 50 years $\times$ 2 seasons.

Table 11: Migration outcomes by age.

Moment	Data	Standard error	Simulation
Age profiles of migration outcomes (MMP):			
number of trips at $16 \leq age < 25$	0.220	(0.016)	0.265
number of trips at $25 \leq age < 35$	0.513	(0.011)	0.507
number of trips at $35 \leq age < 45$	0.536	(0.011)	0.585
number of trips at $45 \leq age < 55$	0.482	(0.012)	0.595
number of trips at $55 \leq age < 65$	0.587	(0.015)	0.605
U.S. experience at $16 \leq age < 25$	0.382	(0.028)	0.401
U.S. experience at $25 \leq age < 35$	0.866	(0.019)	0.893
U.S. experience at $35 \leq age < 45$	0.955	(0.019)	1.157
U.S. experience at $45 \leq age < 55$	0.877	(0.021)	1.174
U.S. experience at $55 \leq age < 65$	0.977	(0.027)	1.139
share in U.S. at $16 \leq age < 25$	0.091	(0.002)	0.074
share in U.S. at $25 \leq age < 35$	0.075	(0.002)	0.063
share in U.S. at $35 \leq age < 45$	0.047	(0.002)	0.038
share in U.S. at $45 \leq age < 55$	0.030	(0.002)	0.026
share in U.S. at $55 \leq age < 65$	0.014	(0.002)	0.017
share of year in U.S. at $16 \leq age < 25$	0.906	(0.008)	0.771
share of year in U.S. at $25 \leq age < 35$	0.855	(0.006)	0.906
share of year in U.S. at $35 \leq age < 45$	0.847	(0.007)	0.981
share of year in U.S. at $45 \leq age < 55$	0.850	(0.011)	0.971
share of year in U.S. at $55 \leq age < 65$	0.846	(0.020)	0.874
share with family in U.S. at $16 \leq age < 25$	0.184	(0.016)	0.022
share with family in U.S. at $25 \leq age < 35$	0.099	(0.009)	0.196
share with family in U.S. at $35 \leq age < 45$	0.077	(0.010)	0.518
share with family in U.S. at $45 \leq age < 55$	0.135	(0.015)	0.491
share with family in U.S. at $55 \leq age < 65$	0.162	(0.027)	0.223
Regression of migrating to the U.S. (MMP) on:			
$\mathbb{1}[16 \leq age < 25]$	0.082	(0.006)	0.055
$\mathbb{1}[25 \leq age < 35]$	0.068	(0.006)	0.034
$\mathbb{1}[35 \leq age < 45]$	0.054	(0.006)	0.025
$\mathbb{1}[45 \leq age < 55]$	0.044	(0.006)	0.024
$\mathbb{1}[55 \leq age < 65]$	0.029	(0.006)	0.026
$\mathbb{1}[family]$	−0.050	(0.006)	−0.005
$\mathbb{1}[works]$	0.006	(0.003)	−0.028
$\mathbb{1}[\textit{been to the U.S.}]$	0.053	(0.002)	0.008
$\mathbb{1}[legal]$	0.095	(0.003)	0.007
Regression of migrating to the U.S., net of age, having been to the U.S. and family status (MxFLS) on:			
$y_{it}/1e6$	−0.516	(0.453)	0.017
$A_{it}/1e6$	−0.146	(0.253)	0.279

Data moments obtained from the MMP and the MxFLS as indicated. Simulation based on 40,000 agents × 50 years × 2 seasons.

Table 12: Assets and debt.

Moment	Data	Standard error	Simulation
Regression of having non-negative assets (MxFLS) on:			
$\mathbb{1}[16 \leq age < 25]$	0.802	(0.022)	0.961
$\mathbb{1}[25 \leq age < 35]$	0.792	(0.018)	0.836
$\mathbb{1}[35 \leq age < 45]$	0.782	(0.018)	0.842
$\mathbb{1}[45 \leq age < 55]$	0.830	(0.018)	0.830
$\mathbb{1}[55 \leq age < 65]$	0.864	(0.018)	0.847
$\mathbb{1}[family]$	0.001	(0.017)	-0.031
Regression of log assets (MxFLS) on:			
$\mathbb{1}[16 \leq age < 25]$	4.202	(0.220)	6.000
$\mathbb{1}[25 \leq age < 35]$	4.437	(0.186)	6.568
$\mathbb{1}[35 \leq age < 45]$	4.656	(0.181)	6.431
$\mathbb{1}[45 \leq age < 55]$	4.626	(0.186)	6.678
$\mathbb{1}[55 \leq age < 65]$	4.612	(0.193)	7.066
$\mathbb{1}[family]$	0.026	(0.175)	-0.005
Regression of log debt (MxFLS) on:			
$\mathbb{1}[16 \leq age < 25]$	5.214	(0.190)	7.665
$\mathbb{1}[25 \leq age < 35]$	6.324	(0.174)	8.105
$\mathbb{1}[35 \leq age < 45]$	6.838	(0.173)	8.349
$\mathbb{1}[45 \leq age < 55]$	6.986	(0.172)	8.470
$\mathbb{1}[55 \leq age < 65]$	7.057	(0.173)	8.612
$\mathbb{1}[family]$	0.000	(0.168)	-0.040

Data moments are obtained from the MxFLS. Simulation based on 40,000 agents $\times$ 50 years.

Table 13: Unobserved heterogeneity (I).

Moment	Data	Standard error	Simulation
Within-individual mean earnings residual in Mexico (MxFLS):			
1. dec	−1.758	(0.010)	−1.028
2. dec	−0.766	(0.010)	−0.669
3. dec	−0.417	(0.010)	−0.468
4. dec	−0.186	(0.010)	−0.301
5. dec	−0.000	(0.010)	−0.144
6. dec	0.173	(0.010)	0.026
7. dec	0.335	(0.010)	0.218
8. dec	0.510	(0.010)	0.444
9. dec	0.723	(0.010)	0.753
10. dec	1.294	(0.010)	1.170
Within-individual mean earnings residual in the U.S. (SIPP):			
1. dec	−1.250	(0.011)	−0.920
2. dec	−0.557	(0.011)	−0.490
3. dec	−0.337	(0.011)	−0.307
4. dec	−0.165	(0.011)	−0.157
5. dec	−0.019	(0.011)	−0.032
6. dec	0.108	(0.011)	0.083
7. dec	0.220	(0.011)	0.205
8. dec	0.356	(0.011)	0.335
9. dec	0.552	(0.011)	0.495
10. dec	0.952	(0.011)	0.790
Duration of last trip to the U.S. | age (MxFLS):			
1. dec of time in U.S.|age	−0.465	(0.037)	−0.690
2. dec of time in U.S.|age	−0.232	(0.045)	−0.317
3. dec of time in U.S.|age	−0.189	(0.042)	−0.287
4. dec of time in U.S.|age	−0.154	(0.042)	−0.281
5. dec of time in U.S.|age	−0.106	(0.042)	−0.271
6. dec of time in U.S.|age	−0.084	(0.044)	−0.261
7. dec of time in U.S.|age	−0.067	(0.041)	−0.250
8. dec of time in U.S.|age	−0.053	(0.042)	−0.244
9. dec of time in U.S.|age	−0.032	(0.044)	0.106
10. dec of time in U.S.|age	1.441	(0.043)	2.598
Duration of current trip to the U.S. | age (SIPP):			
1. dec of time in U.S.|age	−14.885	(0.146)	−12.429
2. dec of time in U.S.|age	−8.583	(0.147)	−5.681
3. dec of time in U.S.|age	−5.536	(0.146)	−3.588
4. dec of time in U.S.|age	−3.310	(0.147)	−1.998
5. dec of time in U.S.|age	−1.348	(0.147)	−0.452
6. dec of time in U.S.|age	0.454	(0.147)	1.080
7. dec of time in U.S.|age	2.341	(0.146)	2.648
8. dec of time in U.S.|age	4.404	(0.147)	4.398
9. dec of time in U.S.|age	7.265	(0.147)	6.409
10. dec of time in U.S.|age	13.838	(0.147)	9.691

Deciles of residuals from regressions of the indicated variables on a full set of age indicators. Data moments are obtained from the MxFLS and the SIPP as indicated. Simulation based on 40,000 agents × 50 years × 2 seasons.

Table 14: Unobserved heterogeneity (II).

Moment	Data	Standard error	Simulation
Log annual earnings in Mexico by decile of last migration duration (MxFLS):			
1. dec of last migration duration |age	8.197	(0.039)	8.738
2. dec of last migration duration |age	8.048	(0.047)	8.718
3. dec of last migration duration |age	8.143	(0.046)	8.693
4. dec of last migration duration |age	8.148	(0.044)	8.679
5. dec of last migration duration |age	8.081	(0.044)	8.682
6. dec of last migration duration |age	8.300	(0.044)	8.675
7. dec of last migration duration |age	8.124	(0.043)	8.688
8. dec of last migration duration |age	8.261	(0.043)	8.605
9. dec of last migration duration |age	8.334	(0.045)	8.793
10. dec of last migration duration |age	8.214	(0.046)	9.428
Log annual earnings in the U.S. by decile of current migration duration (SIPP):			
1. dec of time in U.S.|age	9.335	(0.051)	9.423
2. dec of time in U.S.|age	9.556	(0.060)	9.354
3. dec of time in U.S.|age	9.548	(0.054)	9.312
4. dec of time in U.S.|age	9.743	(0.054)	9.320
5. dec of time in U.S.|age	9.711	(0.057)	9.494
6. dec of time in U.S.|age	9.910	(0.058)	9.517
7. dec of time in U.S.|age	9.722	(0.047)	9.588
8. dec of time in U.S.|age	9.986	(0.055)	9.636
9. dec of time in U.S.|age	9.979	(0.070)	9.678
10. dec of time in U.S.|age	9.993	(0.067)	9.812

Data moments obtained from the MxFLS and the SIPP as indicated. Simulation based on 40,000 agents $\times$ 50 years $\times$ 2 seasons.

Table 15: Weights for non-representative samples.

Moment	Data	Standard error	Simulation
Being in the U.S. | age in the MMP:			
1. dec	−0.089	(0.001)	−0.074
2. dec	−0.078	(0.001)	−0.067
3. dec	−0.065	(0.001)	−0.057
4. dec	−0.053	(0.001)	−0.047
5. dec	−0.045	(0.001)	−0.038
6. dec	−0.037	(0.001)	−0.031
7. dec	−0.028	(0.001)	−0.027
8. dec	−0.018	(0.001)	−0.020
9. dec	0.024	(0.001)	−0.017
10. dec	0.395	(0.001)	0.391
Log biannual earnings in Progresa:			
1. dec	6.374	(0.010)	6.387
2. dec	7.186	(0.010)	6.974
3. dec	7.578	(0.009)	7.315
4. dec	7.813	(0.011)	7.541
5. dec	7.975	(0.010)	7.795
6. dec	8.171	(0.009)	8.076
7. dec	8.360	(0.009)	8.352
8. dec	8.412	(0.056)	8.684
9. dec	8.568	(0.010)	8.914
10. dec	9.176	(0.011)	9.588
Regression of log loan take-up during last 6 months (Progresa) on:			
$\mathbb{1}[\mathit{PROGRESA\ treated}]$	0.432	(0.196)	0.415

The first panel shows deciles of within-individual mean residuals from a regression of being in the U.S. on a full set of age indicators, as reported in the MMP sample. The second panel show deciles of earnings as reported in the Progresa sample. Simulation based on 40,000 agents × 50 years. As a model counterpart for the Progresa treatment, an additional 8,000 agents are simulated. Simulated moments are constructed for those who satisfy the empirical sample selection criteria.

F Structural Parameter Estimates

This appendix lists the full set of structural parameters estimated. I group these into parameters governing family status transitions, legal status transitions, employment transitions in Mexico, employment transitions in the U.S., earnings in Mexico, earnings in the U.S., preferences, migration costs, and the initial stock of assets and debt limits.

Table 16: Structural estimates of family status transition parameters.

Parameter	Point estimate	Standard error
$p_{f+}(\Omega)$:		
ψ_0^{f+}	-1.609	(0.140)
$\psi_{a\leq 30}^{f+}$	0.022	(0.001)
$\psi_{30<a\leq 50}^{f+}$	-0.066	(0.009)
$\psi_{a>50}^{f+}$	0.081	(0.025)
$p_{f-}(\Omega)$:		
ψ_0^{f-}	0.561	(0.033)
$\psi_{a\leq 30}^{f-}$	-0.128	(0.003)
$\psi_{30<a\leq 50}^{f-}$	0.043	(0.006)
$\psi_{a>50}^{f-}$	-0.004	(0.007)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 17: Structural estimates of legal status transition parameters.

Parameter	Point estimate	Standard error
$p_{d+}(\Omega)$:		
$\psi_0^{\delta+}$	-4.608	(0.369)
$\psi_e^{\delta+}$	1.615	(0.123)
$\psi_{a\leq 30}^{\delta+}$	0.102	(0.012)
$\psi_{30<a\leq 50}^{\delta+}$	0.060	(0.033)
$\psi_{a>50}^{\delta+}$	-0.044	(0.004)
$p_{d-}(\Omega)$:		
$\psi_0^{\delta-}$	-2.276	(0.027)
$\psi_e^{\delta-}$	-0.191	(0.374)
$\psi_{a\leq 30}^{\delta-}$	0.002	(0.019)
$\psi_{30<a\leq 50}^{\delta-}$	-0.049	(0.410)
$\psi_{a>50}^{\delta-}$	-0.075	(1.109)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 18: Structural estimates of employment transition parameter for Mexico.

Parameter	Point estimate	Standard error
$\lambda_w(\Omega_{it} \mid e_{it-1} = nw, l_{it} = MX)$:		
$\psi_0^{w,MX}$	2.033	(0.291)
$\psi_s^{w,MX}$	0.090	(0.010)
$\psi_X^{w,MX}$	-0.107	(0.025)
$\psi_{a\leq 25}^{w,MX}$	-0.099	(0.011)
$\psi_{25<a\leq 40}^{w,MX}$	-0.072	(0.006)
$\psi_{40<a\leq 55}^{w,MX}$	-0.092	(0.007)
$\psi_{a>55}^{w,MX}$	-0.045	(0.066)
$\lambda_{nw}(\Omega_{it} \mid e_{it-1} = w, l_{it} = MX)$:		
$\psi_0^{nw,MX}$	-5.526	(0.193)
$\psi_s^{nw,MX}$	-0.015	(0.127)
$\psi_X^{nw,MX}$	-0.056	(0.111)
$\psi_{a\leq 25}^{nw,MX}$	0.094	(0.006)
$\psi_{25<a\leq 40}^{nw,MX}$	0.013	(0.004)
$\psi_{40<a\leq 55}^{nw,MX}$	0.004	(0.008)
$\psi_{a>55}^{nw,MX}$	0.026	(2.783)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 19: Structural estimates of employment transition parameters in the U.S.

Parameter	Point estimate	Standard error
$\lambda_w(\Omega_{it} \mid e_{it-1} = nw, l_{it} = US)$:		
$\psi_0^{w,US}$	0.539	(0.091)
$\psi_X^{w,US}$	-0.005	(0.003)
$\psi_\delta^{w,US}$	-0.030	(0.009)
$\psi_s^{w,US}$	-0.438	(0.106)
$\psi_{a\leq 25}^{w,US}$	-0.009	(0.003)
$\psi_{25<a\leq 40}^{w,US}$	-0.073	(0.007)
$\psi_{40<a\leq 55}^{w,US}$	-0.062	(0.006)
$\psi_{a>55}^{w,US}$	-0.093	(0.098)
$\lambda_{nw}(\Omega_{it} \mid e_{it-1} = w, l_{it} = US)$:		
$\psi_0^{nw,US}$	-2.044	(0.052)
$\psi_X^{nw,US}$	-0.002	(0.002)
$\psi_\delta^{nw,US}$	-0.024	(0.020)
$\psi_s^{nw,US}$	-0.707	(0.116)
$\psi_{a\leq 25}^{nw,US}$	-0.002	(0.001)
$\psi_{25<a\leq 40}^{nw,US}$	0.002	(0.004)
$\psi_{40<a\leq 55}^{nw,US}$	0.010	(0.004)
$\psi_{a>55}^{nw,US}$	0.189	(0.025)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 20: Structural estimates of earnings function parameters in Mexico.

Parameter	Point estimate	Standard error
α_i^{MX}	5.656	(0.100)
	5.785	(0.096)
	6.425	(0.034)
	6.750	(0.124)
$f^{MX}(a)$:		
$\psi_{a\leq 20}^{y,MX}$	0.103	(0.004)
$\psi_{20<a\leq 25}^{y,MX}$	0.051	(0.003)
$\psi_{25<a\leq 35}^{y,MX}$	0.021	(0.002)
$\psi_{35<a\leq 50}^{y,MX}$	0.009	(0.002)
$\psi_{50<a}^{y,MX}$	0.004	(0.003)
σ_u^{MX}	0.905	(0.024)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 21: Structural estimates of earnings function parameters in the U.S.

Parameter	Point estimate	Standard error
α_i^{US}	6.593	(0.484)
	7.424	(0.231)
	7.435	(0.221)
	7.513	(0.190)
$f^{US}(a, X)$:		
$\psi_{x\leq 5}^{y,US}$	0.074	(0.005)
$\psi_{5<x\leq 10}^{y,US}$	0.023	(0.012)
$\psi_{x>10}^{y,US}$	0.013	(0.003)
$\psi_{a\leq 20}^{y,US}$	0.051	(0.003)
$\psi_{20<a\leq 25}^{y,US}$	0.028	(0.003)
$\psi_{25<a\leq 35}^{y,US}$	0.023	(0.004)
$\psi_{35<a\leq 50}^{y,US}$	0.007	(0.003)
$\psi_{50<a}^{y,US}$	0.001	(0.010)
σ_u^{US}	1.301	(0.025)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 22: Structural estimates of preference parameters.

Parameter	Point estimate	Standard error
π_i^{US}	1.291	(0.246)
	0.745	(0.098)
	1.299	(0.083)
	0.603	(0.036)
ϕ_c	0.409	(0.030)
$\phi_{f,l\neq l^f}$	0.409	(0.026)
$\phi_{f,l=l^f}$	5.940	(0.230)
σ_0^{ε}	1.653	(0.077)
σ_a^{ε}	−0.004	(0.002)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 23: Structural estimates of migration cost parameters ($C(\Omega)$).

Parameter	Point estimate	Standard error
γ_0	5.757	(0.172)
γ_a	0.054	(0.001)
$\gamma_{X^{US}>0}$	-3.211	(0.254)
γ_{undoc}	2.156	(0.148)
γ_f	16.917	(0.336)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 24: Structural estimates of borrowing constraint ($B(\mathrm{E}[y^{MX}], \Omega_{it})$) and initial stock of assets parameters.

Parameter	Point estimate	Standard error
δ_0	-2.685	(0.094)
δ_y	2.613	(0.060)
$\tilde{\alpha}_A$	9.265	(0.460)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.

Table 25: Structural estimates of unobserved heterogeneity weights for non-representative data sets ($\{\omega_1^{MMP}, ..., \omega_{T-1}^{MMP}\}$ and $\{\omega_1^{Progresa}, ..., \omega_{T-1}^{Progresa}\}$).

Parameter	Point estimate	Standard error
ω_1^{MMP}	0.404	(0.244)
ω_2^{MMP}	0.093	(0.306)
ω_3^{MMP}	0.213	(0.068)
$\omega_1^{Progresa}$	0.416	(0.385)
$\omega_2^{Progresa}$	0.110	(0.135)
$\omega_3^{Progresa}$	0.197	(0.424)

Estimation by indirect inference, based on 40,000 simulations, standard errors in parentheses.