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ABSTRACT

Borrowing Constraints and the Dynamics of Return and Repeat Migration

As wages in migrant sending countries catch up with those in destinations, migrants adjust on several margins, including their duration of stay, the number of migrations they undertake, as well as the amount saved while abroad. This paper combines Mexican and U.S. data to estimate a dynamic model of consumption, emigration and re-migration, accounting for financial constraints. An increase in Mexican household earnings shortens migration duration, but raises the number of trips per migrant. For lower-income migrants, a rise in Mexican wages leads to a more than proportional effect on consumption expenditure in Mexico, arising from repatriated savings.

JEL Classification: J61, D15, F22

Keywords: migration duration, repeat migration, borrowing constraints

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1 Introduction

Migrations to the United States often are temporary, and many migrants move repeatedly. The size and composition of the immigrant population, and its impact on non-migrants are shaped by these migration dynamics. The desire to leave, return or re-migrate, in turn, depends on economic conditions in the country of origin. If earnings there rise, so does the opportunity cost of leaving. Yet, migration also becomes more affordable for individuals facing credit constraints. Factors like wealth and earnings, which determine the extent to which financial constraints are binding, simultaneously influence whether a return to the home country is desirable for those who have migrated. Understanding the channels by which an increase in earnings levels affects not only emigration, but also subsequent choices such as return migration or savings repatriation is important given the rapid economic development in many lower-income countries. It also is crucial for an assessment of many development policies and income support programs, knowledge of which enters migrants' optimizing behavior. Return and repeat migration are directly linked to other outcomes: temporary migrants may have a stronger incentive to save; repeat migration can facilitate better responses to seasonal or cyclical variation, and thus imply fewer unemployed migrants residing in the U.S.; finally, outcomes such as children's welfare when family stays behind in Mexico may be affected depending on how long a parent is absent.

This paper estimates the effects of earnings in a migrant sending country catching up relative to the destination. Specifically, it evaluates a rise in household earnings in Mexico on emigration, return and re-migration when individuals are financially constrained. An analysis of both emigration and return migration requires data and a model that cover choices and outcomes in both Mexico and the U.S. Since data sets generally do not follow migrants across the border, studies which exploit experimental variation in incomes in Mexico can evaluate the effect on emigration, however not on subsequent decisions, such as how long to stay in the U.S. or how much to save while abroad. To evaluate effects on these choices, I formulate a dynamic model of saving and borrowing, and of both individual and family location choices. This more structural framework allows me, first, to draw on both Mexican and U.S. data sources in the estimation of the model's parameters. Second, it allows an evaluation of responses in choices made in the U.S. to changes in outcomes in Mexico, and the results in this paper imply that economic conditions in a migrant's country of *origin* need to be accounted for also in analyses of migrants' economic behavior in the *destination*. Third, the model allows a disentangling of mechanisms behind the net effects identified by experimental studies. Finally, its structure allows identification of crucial parameters such as the cost of migration. The model accounts for unobserved heterogeneity in agents' productivity and in their migration preference. This allows for an evaluation of the effect of earnings changes not only on migration behavior, but also on the composition of the migrant population.

An important factor for location choices is the unobserved monetary cost of migration, the identification of which is inherently related to modeling asset accumulation, as well as households' credit access. If households can borrow up to an *unknown* limit, it is unclear whether an observed migration has been facilitated by low migration costs or by a generous credit limit. Comparable studies estimating migration costs thus assume that individuals cannot borrow. 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.

The fact observed in the data that households with higher labor income hold more debt suggests that a household's access to credit may depend on its income. To achieve identification of such income dependence in credit access despite a potential correlation of individual productivity with the unobserved innate 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 shifter affects both borrowing and the probability to emigrate, randomized cash transfers provide income variation that is credibly uncorrelated with innate preferences. The treatment effect of the program on borrowing is used as an additional moment in the estimation of the model, which together with migrations observed along the wealth distribution allows a joint identification of migration costs and debt limits. Since the survey did not follow individuals across the border, randomized variation from the program cannot be used to identify the effect of income on migration duration and repeat migration. Rather, the analysis of migration dynamics requires a more structural approach which models choices in the destination country in conjunction with outcomes at the 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.

The estimation further uses data from the Mexican Family Life Survey, the U.S. Survey of Income and Program Participation and the Mexican Migration Project. I explicitly address the non-representativeness of some of the surveys via a flexible and novel estimation of unobserved heterogeneity types. In particular, I let the model reflect different sample compositions in terms of unobserved productivity and preferences when constructing estimation moments from different samples. This is in addition to selection on a rich set of observables state variables in the model. I then use the estimated model to evaluate the effects of higher earnings in Mexico on return and repeat migration, as well as on migrants' saving behavior.

Contrary to a model without financial constraints, in which an increase in origin earnings would unambiguously decrease migration, I find that higher earnings in Mexico raise both emigration and the number of trips per migrant. The effect on emigration is inverted U-shaped along the wealth distribution, in line with reduced form evidence. That is, constraint relaxation dominates at intermediate wealth levels, whereas the increased opportunity cost of migration weakens this effect at the upper tail of the distribution. At very low levels of wealth, modest gains in earnings are often insufficient to overcome the constraint. Reduced form analysis identifies the net effect of these mechanisms. Using information on both saving and location choices in the estimation of the structural model instead allows identification of preference parameters and constraints, and hence to distinguish different 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 earnings at the destination only will offset the effect of a rise in earnings at the origin if financial constraints are negligible. I find that, conditional on ever migrating, a 10% increase in Mexican earnings raises the average number of trips by 4.1%, resulting again from a relaxed constraint. The average time spent in the U.S. per trip, however, is shortened by 6.9%, as the opportunity cost of time spent abroad has increased. These patterns are confirmed by a validation exercise based on observed variations across Mexican municipalities. Income variation across communities may derive from variation in climatic conditions, crop types or the access to manufacturing jobs in nearby cities. Observing the same relation as predicted by the structural model between incomes on the one hand and migration duration and the number of trips per migrant on the other is reassuring, and suggests similar effects for different sources of income variation. Finally, I 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 returning migrants. I show that accounting for credit access is empirically important, and that a model without borrowing may underestimate the cost of migration by almost 30%.

This paper contributes to the literature that uses dynamic life cycle models to analyze aspects of temporary international migration. Papers by Colussi (2003), Thom (2010), Nakajima (2015), Lessem (2018), and Kovak and Lessem (2020) focus on the effects of border enforcement and visa policies on Mexico-U.S. migration. Bellemare (2007) and Rendon and Cuecuecha (2010) investigate job search and outmigration of immigrants in Germany and the U.S., Kırdar (2012) evaluates the social insurance contribution of Turkish migrants in Germany, whereas Adda et al. (2021) examine human capital investment.[1] For the context of internal migration in Indonesia, Kleemans (2015) estimates a dynamic model and confirms the importance of liquidity constraints. Beside the differences in the questions examined in these studies, the distinguishing features of the model used here include that I account for borrowing, that asset accumulation and migration of family members 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. The latter is important since many Mexicans work in seasonally volatile sectors, a variation that does not average out in non-linear models.

The effects of origin earnings on post-emigration choices like saving, migration duration, or subsequent migrations are of immediate policy relevance to both origin and destination countries. My paper thus complements studies that estimate the effect of an income shock on emigration. For Mexico-U.S. migration, Angelucci (2015) estimates the effect of Progresa on emigration. Going beyond this, I disentangle the rise in the opportunity cost of migration and the relaxation of financial constraints, and estimate the dynamic effects on post-emigration choices like return migration and savings accumulation. In a different context, Bazzi (2017) uses rainfall and commodity price shocks in Indonesia to evaluate determinants of emigration. In line with the existence of financial constraints, he finds a positive effect of income on emigration

[1] See Dustmann and Görlach (2016) for a survey of this literature. Comparable models also have been used to analyze *internal* location choices (see e.g. Kennan and Walker, 2011; Buchinsky et al., 2014; Amior, 2019; Morten, 2019; Oswald, 2019).

from villages with more small landholders. None of these papers consider the effects on return or repeat migration. More broadly, my analysis adds to the evidence that choices and outcomes in the origin country and the destination are tightly interlinked, as documented also by Albert and Monras (2019), who relate origin price levels to the location choice of migrants within the United States.

Methodologically, my work adds to a literature combining structural models with experimental variation. While some studies use treatments of sub-populations to examine the external validity of structural models estimated on the non-treated sample (e.g. Todd and Wolpin, 2006; Kaboski and Townsend, 2011), exogenous variation can also be used for identification of model parameters that are not well-identified from observational survey covariations alone (as in e.g. Attanasio et al., 2012; Huck et al., 2015; Gole and Quinn, 2016; Cahuc et al., 2018). 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 separated from preferences for migration. The experiment thus allows a more flexible specification of the structural model regarding access to credit and unobserved heterogeneity. The 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 and Section 3 the model on which the results are based. Section 4 discusses 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 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 variation in income that can be separated from the demand for credit to pay migration. The estimation thus combines data from four main sources.

Mexican Migration Project (MMP). While there is a lack of representative data sets that track migrants across international borders, the MMP's complete retrospective life histories contain detailed information on employment, family status and migrations for each household head and spouse. I restrict observations to the years 1996-2007, which avoids contamination of results by the 1994 peso crisis and the most abrupt economic woes that followed.[2] I exclude individuals who were born in the U.S. and focus on male household heads aged 16-64 without tertiary education. Information on migrations of spouses is used to identify dependent family members' location. The focus on individuals without college education yields a more homogeneous population to which the model of Section 3 is applied, and allows an exclusion of student migration.[3] Figure A1 in Appendix A.1 illustrates the prevalence of repeat migration and shows the distribution of migration durations. The MMP is representative only within the communities surveyed, whereas these communities are a non-random selection within Mexico. I explicitly address this in the estimation as explained in Section 4.2, also utilizing representative data sources.

Mexican Family Life Survey (MxFLS). As a nationally representative data set, I use the 2002 and 2005 waves of the longitudinal MxFLS. Among its rich information, the MxFLS reports whether and for how long individuals have been to the U.S.[4] If migration is costly, it becomes an investment decision that is plausibly subject to similar financial constraints as entrepreneurial or human capital investments (cf Kerr and Nanda, 2009; Lochner and Monge-Naranjo, 2012). Indeed, imperfect credit markets have been highlighted as an important constraint to migration (McKenzie and Rapoport, 2010; Fernández-Huertas Moraga, 2011; Bazzi, 2017; Gazeaud et al., forthcoming; Rojas Valdés et al., 2020). Earlier studies modeling the asset accumulation of migrants rule out borrowing. While this may be plausible for individuals at

[2]This restriction further excludes a series of policy changes since the 1986 Immigration and Control Act 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 (Gathmann, 2008). Following the Secure Fence Act signed in late 2006, the following years saw the construction of fences along extended parts of the border (Allen et al., 2018). The 2008 Consequence Delivery System or the 2010 Arizona SB 1070 are also past my time window (for details, see Hoekstra and Orozco-Aleman, 2017; Bazzi et al., 2021).

[3]Given the other restrictions, less than 8% of individuals in the MMP sample are tertiary educated; in the nationally representative Mexican Family Life Survey, this applies to less than 11%.

[4]A comparison to the 2006 round of the larger (but not longitudinal) 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% in the ENADID, while it is 1.62% in the MxFLS sample. In the non-representative MMP data, the share is 2.16%, a difference the model will be able to explain.

the low end of the earnings distribution, Figure 1a shows that a considerable share of households in the MxFLS sample report holding negative net assets.[5] Debt limits for these individuals thus must be at non-zero levels, and possibly for others, who do not *choose* to borrow, too.[6] Panel (b) of the Figure further suggests a positive relation between debt and earnings. Specifically, it shows the unconditional cumulative distribution of debt, separately for households with above and below median earnings, as well as the mean debt levels. Conditional on net assets being negative, high earning households have an on average about 25% higher debt level than households with earnings below the median. Unconditional, the difference in debt held is almost 50%. Appendix A.2 confirms the same positive relation conditional on observables. Naturally, data collected in Mexico can be representative at best for the resident population, while missing migrants who are absent at the time of the survey. My empirical framework accounts for this by explicitly modeling location choices.

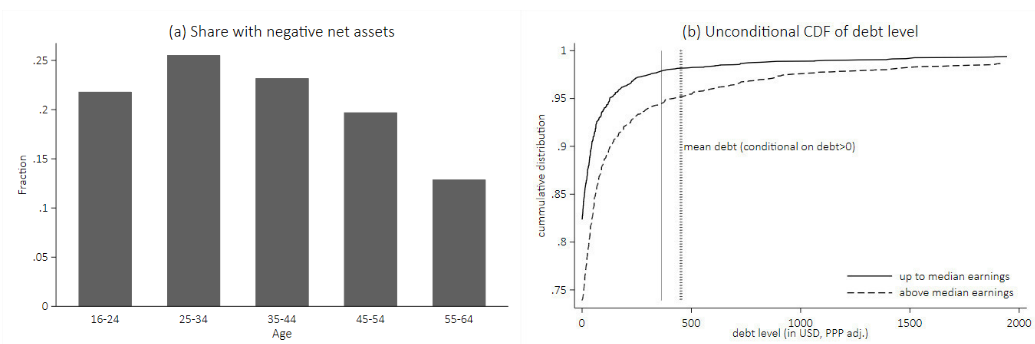

Figure 1: Assets and debt. Debt is calculated as negative net assets (in PPP adjusted USD). The figure shows (a) the fraction of individuals with negative debt by age; (b) the *unconditional* cumulative distribution of debt for households with above and below the median earnings; vertical lines indicate mean debt levels (*conditional* on debt being positive). Source: MxFLS, 2002, 2005.

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. In line with the above restrictions, I use the three SIPP panels 1996-2001, 2001-2004 and 2004-2007. A large share of Mexican migrants work in seasonally volatile sectors, and the monthly information provided by the SIPP is suitable to also assess the importance of this. Appendix Figure A3 confirms this sea-

[5]In computing any of the statistics below, the top 1% of asset holdings has been dropped.
[6]See also Friebel and Guriev (2006) for a theoretical analysis of debt-financed migration.

sonality empirically, by showing the monthly employment rate of Mexicans observed in the SIPP, as well as the number of monthly apprehensions along the southern border. Seasonality in the scale of migration or in the size of the Mexican workforce in the U.S. alone may derive from either demand or supply factors. The seasonal variation in employment *rates* together with the parallel variation in immigration, however, is a strong indication of at least some degree of seasonality in the *demand* for Mexican labor in the U.S.; see also Borjas et al. (1991) for a historic account of this seasonality. The ensuing variation in job prospects directly affects the expected profitability of migration. Accounting for this feature of Mexico-U.S. migration, and allowing for seasonal variation in job offer and loss probabilities is important for the analysis of temporary migration, not only to obtain a more accurate picture, but also since seasonality will not average out in non-linear models.[7]

The main variables used from each of these three 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 the full pooled sample and (retrospective) observation points when an individual is in the U.S. The first entry shows the strong tendency to migrate from communities sampled by the MMP, with 5.2% of individuals spending at least part of any year in the U.S. The MMP further inquires about remittances and saving repatriated after the last trip and their purpose. About 16% report debt repayment as one motive, which includes debt accumulated prior to migration.

Panels (b) and (c) respectively list variables used from the MxFLS and the SIPP. As shown in Figure 1a, more than one fifth of the Mexican population report having negative net assets, with debt levels averaging 432 USD (all monetary variables are PPP adjusted). Among individuals under the age of 35, who are more likely to migrate, the fraction holding negative assets is higher (24.8%). Immigrants surveyed by the SIPP have been to the U.S. on average for 16.7 years. This is considerably more than the average total time abroad 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. The SIPP samples the civilian,

[7]Existing dynamic models of international migration abstract from seasonality, which has received more attention in analyses of internal migration (Bryan et al., 2014; Meghir et al., 2015; Munshi and Rosenzweig, 2016; Rosenzweig and Udry, 2019; Lagakos et al., 2018; Imbert and Papp, 2020).

non-institutionalized population of the United States, irrespective of their legal status. However, 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. The latter provide information on migration duration for large repeated cross-sectional samples of immigrants in the United States and are less prone to sampling bias or 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 similar to the number computed for the SIPP sample.[8] Finally, average earnings of Mexicans in the U.S. are about 1.5 log points higher than in Mexico, suggesting a strong incentive to migrate for many individuals and/or a positive selection of migrants. Note that although some of these sources provide retrospective information, for instance about past migrations, they do not follow individuals across international borders. For the purpose of this paper, it is essential to (i) exploit information from different locations, and (ii) to specify a model that accounts for the selection into each, and which is flexible enough to accommodate heterogeneity across the targeted populations for each sample.

Progresa evaluation data. The positive correlation between earnings and debt shown in Figure 1 can result either from better credit *access* for individuals with higher earnings, or from a higher *demand* for credit by high earning individuals because of different preferences. The latter for instance could come about if individuals with higher earnings also have a stronger preference for migration. One way to assess whether the positive relation is a mere product of the latter is to use data on borrowing in response to experimental variation in incomes that is plausibly orthogonal to unobserved innate preferences. To this end, I draw on evaluation data from Progresa, an initially randomized conditional cash transfer program in Mexico. 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

[8] The SIPP also provides information about respondents' visa category. Hall and Greenman (2013) and Altman et al. (2020) infer the absence of a legal residence permit from the residual response "other", conditional on no other information suggesting otherwise. Following this procedure, studies find little difference between the SIPP sample of (likely) undocumented immigrants and independent data sources (Bachmeier et al., 2014). Instead, the MMP explicitly lists non-documentation as a response category, and I rely on that information rather than the more indirect one from the SIPP.

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
Purpose was debt repayment	0.163	0.369
Paid coyote by himself**	0.504	0.500
Individuals	1,291	

(b) Mexican Family Life Survey (MxFLS)

Variable	Mean	Standard deviation
Been to the U.S.	0.086	0.280
Last migration duration (in years)	1.875	3.996
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.)	971.478	6,225.630
Has debt	0.209	0.407
Amount of debt (in USD, PPP adj.)	432.231	1,585.955
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. Samples include non-tertiary educated Mexican-born male household heads aged 16-64. SIPP statistics (other than "Working") are based on the March survey. Individuals are considered working in a given half-year if working for at least 4 months. Values are deflated to 2005, and adjusted by purchasing power parities if referring to Mexico.

* Conditional on ever having been to the U.S.; ** Conditional on having used a coyote.

up to the age of 14, of whom over 97% attended school even in the absence of the program. For the estimation, I thus restrict the sample to these families.

Information on differential loan take-up in treatment and control communities reveals 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 2 depicts the conditional density of these recent loans to eligible families in the two groups of locations, showing a clear right shift in the distribution for program locations.[9] A plausible explanation is that Progresa transfers improve the capability to repay loans and thus serve as collateral for lenders. In addition, credit access may also be enhanced for non-eligible families via spillovers through increased capital availability in treatment communities, in the spirit of Angelucci and De Giorgi (2009).

In Appendix F, I provide an estimate of the average of this non-parametrically identified treatment effect, which serves as an additional moment in the structural estimation, and allows identification of a more flexible specification of households' access to credit. Note that the experimental variation 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. The program's effect on emigration will, rather than for identification, be used to validate the model.

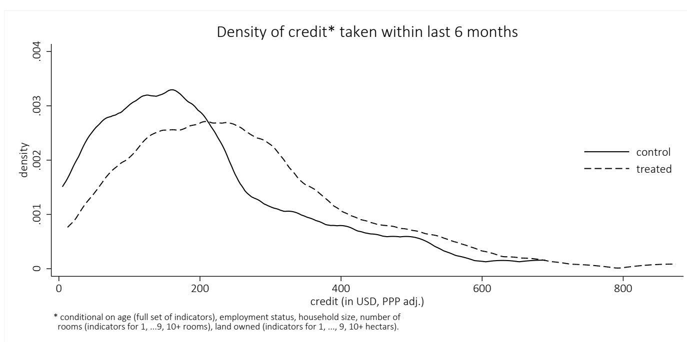

Figure 2: Progresa's monthly cash transfers and new loan take-up. The figure shows the distribution of log amounts of loans taken within the previous 6 months by treatment status. The sample includes male heads aged 16-64 of eligible households with children aged 8-14 attending school. The density is computed using an Epanechnikov kernel with 3/4 of the optimal bandwidth to prevent oversmoothing. Source: Progresa, November 1998.

[9] The graph shows borrowing net of observables as indicated. Appendix A.4 shows the balancing of these variables. Information on borrowing is not available prior to the program.

3 Model

The model is chosen to reflect emigration, return and re-migration behavior in conjunction with asset accumulation and loan take-up under financial constraints, 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. 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. The model keeps track of age a_{it} of household head i at time t, employment status $e_{it} \in \{w, nw\}$, on whether there is dependent family $f_{it} \in \{0,1\}$, current location $\mathbf{l}_{it} \equiv \left(l_{it}, l^f_{it}\right) \in \{MX, US\}^2$ of head and family, legal status in the U.S. $d_{it} \in \{0,1\}$, total U.S. experience X^{US}_{it}, the accumulated stock of assets A_{it}, and current season $s_t \in \{summer, winter\}$. Furthermore, decisions are based on information not observed by the econometrician, including an individual's productivity in different locations, $\alpha_i \equiv \left(\alpha^{MX}_i, \alpha^{US}_i\right)$, preferences π^{US}_i towards the destination country, and transitory shocks to earnings and locational preference, v^l_{it} and $\varepsilon^{\mathbf{l}}_{it}$. The vector $\Omega_{it} \equiv (a_{it}, e_{it}, f_{it}, \mathbf{l}_{it}, d_{it}, X^{US}_{it}, A_{it}, s_t, \alpha_i, \pi^{US}_i, v^l_{it}, \varepsilon^{\mathbf{l}}_{it})$ collects the state variables observed by an agent at time t, though some of this information is revealed sequentially within the period, as detailed below and described in Appendix Figure A4. 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 $p_{f-}(age_{it})$.[10] Also at the beginning of the period, individuals learn whether they have a legal permit to live and work in the U.S. Transition 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. I allow for the loss of legal status to accommodate the fact that permits can be temporary. The timing in the model is such that after family and legal status are known, taste shocks $\varepsilon^{\mathbf{l}}_{it}$ are realized and household members choose a location. U.S. border enforcement makes undocumented migrants face a risk of apprehension, so that attempted migrations fail with probability p_a. When there is dependent family,

[10]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.

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% of the reverse. I thus exclude this option. To further save on computation time, I assume that all family members share the same legal status in the United States. For married migrants sampled by the MMP this is true in 96% 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 season to accommodate varying aggregate labor demand. Both functions are location specific, and in the U.S. also depend on a worker's legal status. While employment probabilities are endogenous to agents' emigration and migration duration choices, job offers are always accepted when they arrive. I focus on the extensive margin of employment of male household heads and assume that they either work full time or do not work.[11] 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 for migrants of cumulative time spent in the United States. Idiosyncratic shocks to log earnings, v_{it}^l, are independent and normally distributed across time and individuals, with mean zero and variance $\sigma_{v^l}^2$, and are revealed only after a location has been chosen. 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

[11] I also abstract from the labor market status of spouses, whose employment rate in the MMP sample of non-tertiary educated individuals however is rather low, at 19.96%.

of labor market shocks. I assume a standard inter-temporal 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},

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

with real interest rate r. A household's initial asset level is related to productivity and given by $A_{i0} = \tilde{\alpha}_A \exp(\alpha_i^{MX})$, where $\tilde{\alpha}_A$ is an estimated parameter. To account for differences in currency purchasing power, the stock of assets is adjusted by the relative price level at the time of a (re-)migration.[12] Whereas return to Mexico is costless, the monetary cost of migrating from Mexico to the U.S. is

$$C(\Omega_{it}) = \gamma_0 + \gamma_a a_{it} + \gamma_{undoc}(1 - d_{it}) + \gamma_X \mathbb{1}[X_{it}^{US} > 0],$$

which varies with age, legal status and previous U.S. experience. An earlier stay in the U.S. may lower the cost of re-migration, for instance because initial information constraints are overcome.[13] For family migration, the cost may differ, and is given by $C^f(\Omega_{it}) = C(\Omega_{it}) + \gamma_f$. When a household head is in Mexico, the household may 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 Figure 1, I let this limit vary with (expected) earnings.[14] I further assume that the constraint becomes tighter towards the end of life, enforcing a repayment of debt at older ages (see Appendix B for details),[15] and that migrants

[12]For agents with dependent family, I assume that the family location determines the price level of assets and consumption. The narrow time window to which the estimation samples are restricted excludes both the peso crisis and the financial crisis, and I assume that agents expect economic outcomes, including wages and the purchasing power of USD in Mexico, to stay at their mean level during the years 1996-2007. Assets accumulated in the U.S. are accordingly adjusted by a factor 1.639 to account for lower price levels in Mexico (see Appendix B for details).

[13]A similar argument has been made by Bryan et al. (2014), who find a higher probability of consecutive rural-urban migrations in Bangladesh after the cost of an initial trip has been covered.

[14]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}.

[15]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.

cannot borrow while abroad. Emigration of a household head then requires that[16]

$$(1+r)A_{it-1} - C(\Omega_{it}) \quad \geq \quad -B(\mathrm{E}[y_{it}^{MX}], \Omega_{it}). \tag{2}$$

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 current assets, or whether migration costs are in fact higher and households can borrow to partly pay for the migration. Identification thus requires information on borrowing, as is available in the MxFLS, to pin down B.

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 f_{it} indicates whether there is dependent family. If so, utility from consumption is scaled by $\phi_f^{\mathbf{l}} = \phi_f^{l \neq lf}$ if families are spatially separated, and $\phi_f^{\mathbf{l}} = \phi_f^{l=lf}$ if not. Besides a disutility of separation from family, the scaling of consumption by $\phi_f^{\mathbf{l}}$ captures variation in consumption efficiency that can arise for instance due to different living arrangements while the household head is abroad. 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 when in the U.S. relative to marginal utility from consumption in Mexico.[17] In addition to this time-constant heterogeneity in location preferences, households face transitory preference shocks $\varepsilon_{it}^{\mathbf{l}}$ for each location. 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 a spread parameter, specified as a linear

[16] The left hand side of (2) is expanded by $C^f(\Omega_{it})$ for migration of dependent family. The borrowing constraint also applies to consumption choices, which must ensure that $A_{it} \geq -B(\mathrm{E}[y_{it}^{MX}], \Omega_{it})$. When agents are in the U.S., they cannot borrow, but may carry on debt accumulated in Mexico.

[17] This parameter also picks up different returns to consumption for the agent if part of consumption accrues to extended family through remittances.

function of age.[18] The preference components π_i^{US} and $\varepsilon_{it}^{\mathbf{l}}$ capture constant and time-varying valuations of unobserved location characteristics.

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

$$V(\Omega_{it}) = \max_{\substack{c_{it} \geq 0 \\ \mathbf{l}_{it} \in \{MX, US\}}} \quad u_{it}(c_{it}, \Omega_{it}) + \beta \mathrm{E}_t \left[V(\Omega_{it+1}) \right],$$

where β discounts future expected utility. Transitions for the persistent stochastic state variables in Ω_{it} are governed by $\lambda_w(\Omega_{it})$, $\lambda_{nw}(\Omega_{it})$, $p_{f+}(\Omega_{it})$, $p_{f-}(\Omega_{it})$, $p_{d+}(\Omega_{it})$ 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}, which they reach in period $\bar{t}$. The terminal value is given by $V(\Omega_{i\bar{t}} | a_{i\bar{t}} = a^{end}) = \phi_A A_{i\bar{t}}^{\phi_c}$, with a bequest motive if $\phi_A > 0$.

Several features of the model can make temporary migration an optimal choice for agents. Changes in employment or family status, preference shocks and seasonality in labor demand can lead to emigration, return and repeat migration. Besides these, agents may—despite persistently higher earnings levels in the U.S.—decide to migrate only temporarily if they derive a higher utility from consumption in Mexico. Finally, migrating temporarily may be optimal if savings accumulated in the U.S. have a higher purchasing power in Mexico, where prices are lower. In both cases, migration serves the purpose of asset accumulation, which can be achieved faster abroad.

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 95 free parameters of the model by minimizing the distance of 233 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,

[18] Additivity of ε in the utility function, independence and extreme value distribution imply that location choice probabilities take a logistic form, with the value functions of being in the home and host country, respectively, as arguments (Rust, 1987).

important econometric issues arise, which are addressed in Section 4.2.

Before that, I discuss parameter identification. Given the rich set of unobserved components in the model, three key assumptions are required: (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 for the same individual; (2) agents move based on expected earnings before transitory earnings shocks v_{it}^{l} are observed; (3) the randomized treatment assignment of Progresa is uncorrelated with the innate preference π_i^{US} 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 from the program. In what follows, identification is discussed more comprehensively. Additional details are relegated to Appendix F, where Table A2 systematically lists all parameters and the identifying moments, and Figure A7 graphically shows the gradient matrix of all moments with respect to the model's parameters.

4.1 Identification

Transition probabilities and earnings function. Most parameters are closely related to conditional moments observed in the data. To identify parameters governing transitions in family status (p_{f+}, p_{f-}), legal status (p_{d+}, p_{d-}) and employment (λ_w, λ_{nw}), I match coefficients from OLS regressions of observed transitions in these outcomes on state variables that determine them. Note that due to endogenous selection into locations, and thus either Mexican or U.S. samples, all parameters, including those listed above, need to be estimated jointly within the model (similar, e.g., to Del Boca et al., 2019). Parameters of the earnings function are identified through regressions of log earnings in Mexico and the U.S. on arguments of $f(\cdot)$. The joint distribution of earnings and past migration experience in the two waves of the MxFLS does not allow a separate identification of (i) returns in Mexican earnings to having been to the U.S. on the one hand, and (ii) 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.[19] The flexible specification of unobserved heterogeneity allows for

[19]The literature is 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

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 assuming a discrete number of types of agents, who differ in preference and productivity. The longitudinal dimension of earnings data in the MxFLS and the U.S. SIPP data identifies the marginal distributions of productivities α_i^{MX} and α_i^{US}. Time spent in the U.S. helps to identify the marginal distribution of preferences π_i^{US} for being abroad. In addition, the estimation targets the joint distributions of past migration experience and mean earnings residuals in Mexico from the MxFLS, and of U.S. experience and mean earnings residuals in the U.S. from the SIPP. These latter two sets of moments link productivities 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 individual*, however, the restriction has to be imposed that the rank within 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. In our sample, Mexicans who later are observed to migrate are wealthier pre-migration (Figure A2b). This relation identifies the monetary cost $C(\Omega_{it})$ of migration *if access to credit is specified*. A more restrictive model ruling out borrowing ($B = 0$), would attribute observed emigrations to a lower cost of moving than a model that allows for borrowing. The empirical relevance of this bias is demonstrated in Appendix C, where a more restrictive model without borrowing is shown to underestimate the monetary cost of migration by almost 30%.

The MxFLS reports household debt, which can identify the *level* of credit limits. However, based on Figure 1b, the model further allows access to credit to depend on income. This *slope* with respect to income creates an additional identification problem: 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, a positive correlation between earnings and debt could either be generated by better credit *access* for individuals with higher earnings (i.e. a positive slope parameter), or by these individuals' higher *demand* for credit. Identi-

on the selection process, Lacuesta (2010) argues that observed earnings differences between Mexican non-migrants and returnees are likely the result of selective emigration.

fication requires either restrictions on heterogeneity, or a source of income variation that is uncorrelated with unobserved preferences. Simple survey covariation would be sufficient to identify the income dependence of debt limits in a simpler model that imposes orthogonality between the dimensions of unobserved heterogeneity.

To avoid such a restriction, I exploit the randomized introduction of Progresa cash transfers in Mexico. This program provided continuous income streams and thus a potential collateral for credit. Specifically, I include the effect of the program on borrowing (see Appendix F) among the moments targeted in the structural estimation. For a given set of parameters, and conditional on income and other observables, the model implies a demand for credit. Conditional on this demand, the covariation of income induced by the program and observed borrowing identifies the income dependence of credit access.[20] Other moments contribute inference of borrowing constraint parameters as well. In fact, Appendix Figure A7 shows in row 88 that the gradients of most moments with respect to the slope parameter of the borrowing constraint are non-zero. The sensitivity measure proposed by Andrews et al. (2017) suggests that δ_y is most sensitive to the fraction of households holding debt and to the amount of debt held, in particular for households with a head younger than age 35 (see also Figure A9). Yet, basing identification purely on non-Progresa moments would imply that it is achieved only through functional forms within the model structure.

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, however, describes the entire population of Mexican-born male household heads without tertiary education, as are moments generated from the MxFLS and the U.S. SIPP data (conditional on individuals' location choice). The model accounts for selection into locations where surveys are collected, and simulated moments throughout are constructed for indi-

[20]Identification 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.

viduals satisfying sample selection and treatment criteria in terms of observables.[21]

Samples may also differ in individuals' unobserved characteristics. The lower income of households covered by Progresa is the most obvious deviation from representativeness, while the main critique against the MMP is its bias toward communities with a high prevalence of migrants. Lower earnings and a higher migration propensity correspond closely to the dimensions of unobserved heterogeneity in the model. In the estimation, heterogeneity is implemented as different types τ of agents in the simulated population, each with distinct values for α_τ^{MX}, α_τ^{US} and π_τ^{US}. To account for the non-representativeness of the MMP and Progresa samples, I allow for different weights with which each type enters the simulation of moments that have their empirical counterpart in one of these non-representative samples. This allows, for instance, that a less productive type has a stronger weight 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 observed 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 $(\pi_\tau^{US}, \alpha_\tau^{MX}, \alpha_\tau^{US})$ are fixed, and are identified from the two representative samples. Identification of the weights thus can be achieved by targeting the distribution of one heterogeneity dimension per set of weights only.[22] In the empirical implementation, $T = 4$. Subject to this approximation and the preserved ranking within productivity distributions in Mexico and in the U.S., each dimension of unobserved heterogeneity can be arbitrarily distributed. Yet, the approximation of heterogeneity itself introduces—like any discretization—an approximation error which may constrain the values for some higher order moments of the distribution of unobserved characteristics that the model can generate, see Appendix D for further details.

[21]For instance, simulated agents' age is drawn from the empirical distribution in each survey. In the case of Progresa, a further selection criterion is to have dependent family that resides in Mexico.

[22]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. These dimensions reflect the most obvious deviation from representativeness for the two samples. Other dimensions are used as a validation check for the model in panels (e) and (f) of Figure 3.

Different sample sizes. If all data moments 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 simulation size). The estimation in this paper, however, uses moments from four samples $\varsigma \in \{MMP, MxFLS, SIPP, Progresa\}$ of different sizes N_ς. While consistency is unaffected by this, the derivation of the asymptotic distribution of the estimator requires an assumption on the rate at which samples increase. Appendix E derives the asymptotic distribution under the assumption that 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 $0 < n_\varsigma^s < \infty$.[23]

5 Results

5.1 Model Fit

The left panel of Figure 3a displays the distribution of the number of migrations undertaken until the time individuals were surveyed by the MMP.[24] For comparison, the right panel shows the same distribution simulated by the model. Similarly, Figures 3b and 3c show the empirical and simulated distributions of the time migrants have spent in the U.S., and the level of log annual savings over the life cycle. Figure Figure 3d contrasts the treatment effect of Progresa transfers on the log amount households borrowed in the six months prior to the survey with the corresponding prediction by the model. Figure A10 in Appendix F summarizes the fit for all 233 moments targeted in the estimation, and Tables A4-A11 list the individual moments.

The treatment effect of Progresa on emigration, as estimated by Angelucci (2015), is not used in the estimation of the model, and thus can serve as an additional credibility check. Panel (e) of Figure 3 compares the model's prediction to results by Angelucci (2015), who estimates the effect of Progresa on the propensity to emigrate in a linear probability model across terciles of the predicted wage distribution. She finds that Progresa transfers raise the emigration rate by 0.51 percentage points at the mid-tercile of the predicted wage distribution in surveyed communities, with no effect at the top and bottom terciles. Figure 3e shows that my model's predictions fall

[23] The derivation builds on Angrist and Krueger (1992), Arellano and Meghir (1992), and Ridder and Moffitt's (2007) discussion of the two sample instrumental variables estimator.

[24] Note that this is weakly less than the total number of migrations during an individual's working life, which Figure A1a captures by restricting the sample to individuals aged 65 or older.

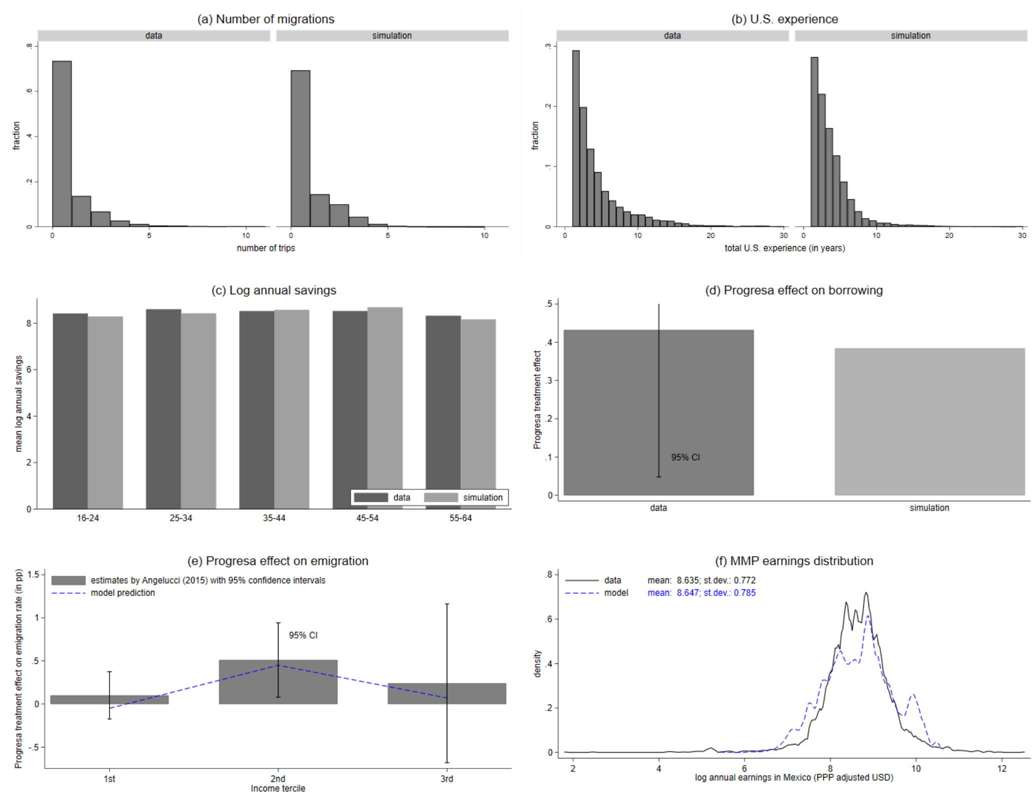

Figure 3: Model fit. (a) Number of migrations at the time of the survey and the corresponding simulation by the model; (b) total time spent in the U.S.; (c) log annual savings by age; (d) effect of Progresa on the log amount borrowed during the past 6 months; (e) comparison to effect of Progresa on emigration estimated by Angelucci (2015) and her 95% confidence intervals; (f) log annual earnings in Mexico predicted by the model (using estimated MMP weights) to that observed in the MMP data. Model predictions are based on 40,000 simulated agents; for panels (a)-(c) and (f), data are from the MMP and simulations drawn from the MMP's age distribution, using estimated weights ω_τ^{MMP}; for panels (d) and (e), data are from the Progresa evaluation sample (see Table A3 for details) and simulations drawn from the Progresa age distribution, with dependent family, and using estimated weights $\omega_\tau^{Progresa}$.

well within Angelucci's confidence bounds. As a further validity check, I compare the earnings distribution observed in the MMP, which is not targeted in the estimation, to its model counterpart. Figure 3f reveals a slightly wider variance of the model prediction, but otherwise little difference between the two.

5.2 Estimates

This section presents the core parameter estimates describing preferences, migration costs and access to credit. A full list of estimates is provided in Appendix G.

Preferences. The top set of estimates in Table 2 shows that 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% ($\pi_3^{US} = 1.300$) to a penalty of 40% ($\pi_4^{US} = 0.604$).[25] The estimate of ϕ_c implies decreasing returns to consumption, with a risk aversion of 0.79, similar for instance to Imai and Keane (2004), who estimate it at 0.74. 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 individuals derive positive utility (suffer a loss) from having family if it resides in the same (a different) location. Since these parameters also subsume variation in consumption efficiency that can arise for instance due to different living arrangements while the household head is abroad, they capture the overall effect of being with or separated from family. Given the curvature ϕ_c, the estimates imply that immigrants are $\left(\phi_f^{l=l^f}/\phi_f^{l\neq l^f}\right)^{\phi_c} - 1 \approx 74\%$ better off having their family with them than if spatially separated. In the model, this rationalizes the fact that—conditional on assets and other observables—individuals are more likely to migrate at younger ages, when they do not (yet) have dependent family.

Borrowing limit. Wider family and social networks in Mexico make it plausible that repayment can be enforced, including in case of migration. To capture this, the debt limit becomes tighter towards the end of life such that repayment is ensured. In addition, households face a constraint to the maximum amount of debt they can hold which is related to their expected earnings (see Section 3 and Appendix B for details). This part of the constraint, specified as $\delta_0 + \delta_y \mathrm{E}[y_{it}]$, is predicted to be the binding constraint in most cases. The estimates in Table 2 imply that only households with half-yearly earnings of at least $-1,000\delta_0/\delta_y \approx 617$ USD have access to credit, with the debt limit rising by $\delta_y/2 \approx 1.4$ USD for every additional USD per year earned. For the earnings quartiles in the MxFLS sample (2,506 USD, 4,351 USD and 6,961 USD, all PPP adjusted), these parameters imply debt limits of respectively 1,893 USD, 4,418 USD and 8,118 USD. This compares to a mean credit card limit reported

[25] The types in Table 2 are ordered by their productivity (see Tables A16 and A17 in the Appendix). For both the MMP and the Progresa sample, the strongest weight is on the lowest productivity type (Table A21), capturing both the lower earnings and assets in those samples.

Table 2: 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})	1.290	(0.042)
preference of type 2 for the U.S. (π_2^{US})	0.744	(0.154)
preference of type 3 for the U.S. (π_3^{US})	1.300	(0.026)
preference of type 4 for the U.S. (π_4^{US})	0.604	(0.026)
returns to consumption (ϕ_c)	0.208	(0.004)
value of bequest (ϕ_A)	0.556	(0.176)
scaling for spatial separation from family ($\phi_f^{l \neq l^f}$)	0.410	(0.022)
scaling for family in same location ($\phi_f^{l=l^f}$)	5.940	(0.253)
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)	-1.749	(0.073)
effect of biannual earnings (δ_y)	2.835	(0.047)
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)	5.760	(0.127)
effect of age (γ_a)	0.057	(0.002)
effect of having been to the U.S. (γ_X)	-3.212	(0.142)
extra cost of undocumented migration (γ_{undoc})	2.157	(0.211)

Note.— Model parameters characterising preferences, access to credit and migration costs estimated by simulated minimum distance estimation based on 40,000 simulated agents × 50 years × 2 seasons. See Section 4.2 for details on standard errors.

by Castellanos et al. (2018) of 49,604 pesos (Table 1), or 6,439 PPP adjusted USD. The additional capital in treated communities might create multiplier effects that raise credit supply. The estimated treatment effect (displayed in Table A3) would then overstate the effect of income on credit access. To show that this theoretical possibility would in fact have little impact on the point estimates of δ_0 and δ_y, I use the sensitivity measure proposed by Andrews et al. (2017) to examine how much these parameters would change if the treatment effect was lower. The sensitivity matrix $\left(\frac{\partial D'}{\partial \vartheta}\big|_{\hat{\theta}} W \frac{\partial D}{\partial \vartheta'}\big|_{\hat{\theta}}\right)^{-1} \frac{\partial D'}{\partial \vartheta}\big|_{\hat{\theta}} W$, which is inversely related to the gradient of moments with respect to parameters, indicates that even a 50% lower treatment effect of Progresa would imply a deviation of less than 0.5% in the estimates of δ_0 and δ_y.[26]

Migration costs. The monetary cost of migration increases with age, and migrants face a lower cost if having been to the U.S. earlier, but a higher one for

[26]This is also due to the steep gradient of the predicted treatment effect with respect to these parameters, see Appendix Figures A7 and A8. Figure A9 shows that the estimate of credit access primarily is sensitive also to the more precisely measured fraction of households holding debt. The full sensitivity matrix amounts to a (95×233)-matrix, and is thus not displayed.

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 $5,760 + 30 \cdot 57 - 3,212 + 2,157 = 6,415$ USD. The estimate for the extra cost of an undocumented migration, γ_{undoc}, is somewhat higher than coyote costs reported in the MMP, but here includes both the direct smuggler cost and other monetary costs associated with an undocumented arrival in the U.S. Part of the lower cost for documented migrations may also be explained by some U.S. visa categories for temporary work, such as H-2A and H-2B, requiring employers to cover transportation costs.

Other estimates, listed in Appendix G, show for instance that earnings profiles in either location are concave over the life cycle (Tables A16 and A17). In addition, U.S. earnings exhibit large returns to U.S. experience, though again at a decreasing rate. This corresponds to patterns that have been documented for various times and contexts (Chiswick, 1978; Borjas, 1985; 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 migrant sending country on migration dynamics. Understanding these effects is important given the economic development in many low- and middle-income countries, but also for an assessment of various development policies and support programs, such as the Mexican Procampo program.[27] 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, the propensity of individuals to move back and forth repeatedly, as well as other choices. Yet, available data—such as the Progresa evaluation sample—do not provide information on post-emigration decisions like whether and when to return to the country of origin. I thus use additional information on economic outcomes and choices from both origin and destination country data to identify preference parameters and constraints in the structural model. The estimated model then allows an evaluation of how strongly different margins of migration and other decisions respond to earnings. Specifically, I simulate the effect of a 10% increase in mean earnings in Mexico. This rise in earnings on average covers 9.85% of the cost of a legal migration without family, or 22.42%

[27] The Programa de Apoyos Directos al Campo (Procampo) is a subsidy program supported by the World Bank that was introduced in 1994 and targets the agricultural, fishing and forestry industries.

of the estimated extra cost if a migrant attempts to cross the border without legal documentation.

Return migration. A rise in earnings expected in the home country not only raises the opportunity cost of staying abroad in terms of origin earnings forgone, but the value of returning is boosted further because individuals know that the future option to emigrate will be more easily affordable if desired. Both these channels tend to shorten migration durations. Panel (a) of Figure 4 shows the fraction of initial arrivals remaining in the country by years since immigration. Whereas the solid curve is the survival rate at baseline, the dashed profile indicates the reduction in migration duration if earnings in Mexico were 10% higher, which shortens the average time continuously spent in the U.S. by more than half a year, or 4.8% when including permanent migrants.This effect is partly driven by compositional changes. Figure 4b 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 6.9%. The reason for the smaller effect for the full population is that the baseline 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 4b to isolate the behavioral response of migrants net of composition changes.

Repeat migration. In the model, repeated migrations can be driven by different factors. An immigrant in the U.S. who has accumulated sufficient savings may find it worthwhile to return and enjoy a higher utility from consumption in Mexico where other family members live. If later 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. An increase in origin country earnings enhances the capacity of individuals to adjust to changing personal and economic conditions. The bottom two panels of Figure 4, which show the distribution of the number of migrations, visualize the effect of an increase in Mexican earnings by 10%. Panel (c) shows the increase when counting all migrations, whereas Panel (d) again isolates 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

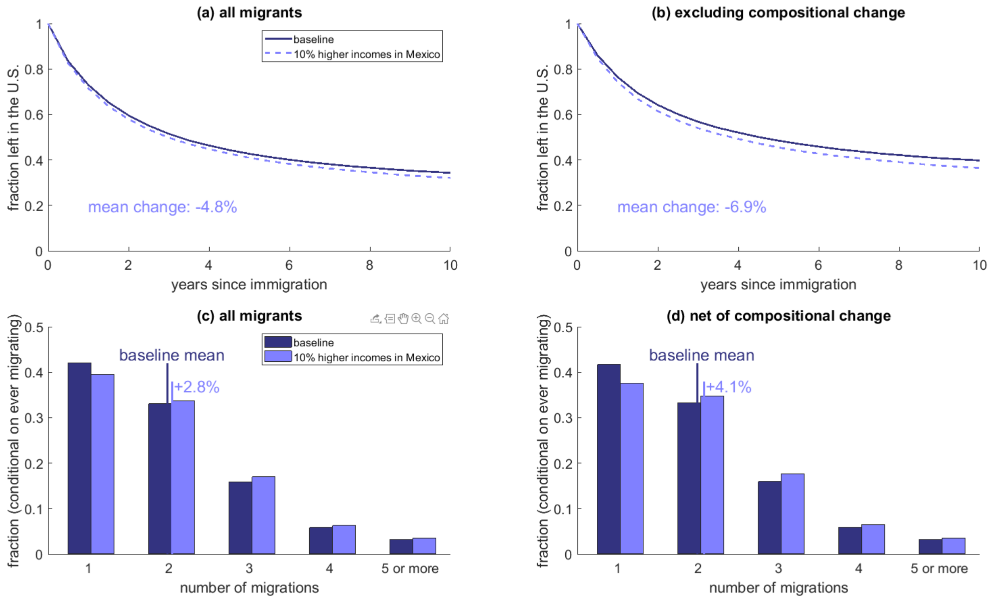

Figure 4: Effects on return and repeat migration. The figure shows for different earnings levels in Mexico (a) survival rates in the U.S. for all Mexican immigrants; (b) survival rates for Mexicans who would have migrated under both earnings levels; (c) the number of migrations for all individuals with at least one migration under the respective scenario; and (d) the number of migrations for individuals with at least one migration in either of the cases considered.

migrated is about two.[28] An increase in earnings by 10% shifts this distribution outward, increasing the average number of migrations by 2.8%. The purely behavioral change for those who are predicted to migrate at least once under either scenario is in fact larger (4.1%). This shows that, first, the relaxation of financial constraints dominates the increased opportunity cost of migration. Second, the effect is driven by the response of individuals who would have migrated even under lower earnings, while compositional changes slightly offset this shift in the distribution.

Globally, neither the effect on migration duration nor that on the number of migrations are linear in earnings. However, an examination of a *decrease* in earnings shows that locally the non-linearity around the observed baseline level of earnings is minor: a counterfactual decrease in earnings by 10% has almost symmetric effects, raising mean migration duration by 5.0% (compared to the 4.8% in Figure 4a), and reduces the mean number of trips per migrant by 3.6% (compared to 2.8% in Figure 4c). Figure 5 shows how these outcomes are affected for larger changes in Mexican

[28] Note that Figure 4 is different from the distribution displayed in Appendix Figure A1a, both due to the non-representativeness of the MMP survey, and its conditioning on migrants having returned.

earnings. In particular, panel (b) of the figure reveals that the effect on repeat migration not only is non-linear, but also non-monotonic, since for very large rises in earnings in Mexico migration becomes increasingly unattractive.

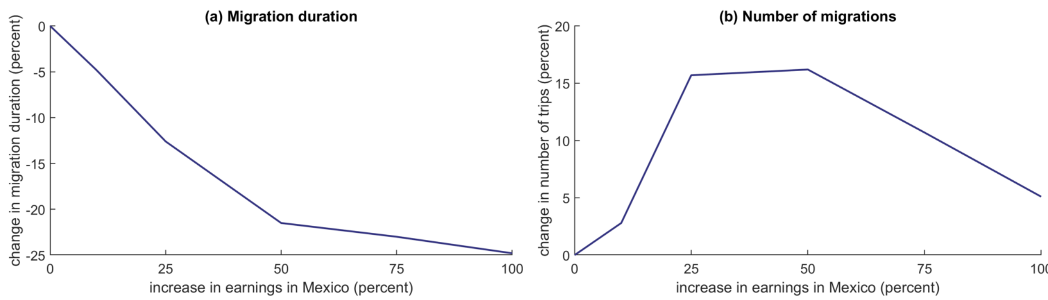

Figure 5: Effects of larger earnings changes. The figure plots percentage changes in (a) mean migration duration and (b) the mean number of trips per migrant for different percentage increases in earnings in Mexico.

The model does not distinguish locations *within* countries. Variation across municipalities can hence serve as a validation check. To confront the predictions in Figure 4 with variation in earnings levels across Mexican municipalities, I collapse the number of trips per migrant, duration of the last trip, as well as earnings to their means within each community surveyed for the Mexican Migration Project.[29] Figure 6 confirms the sign of the relations predicted by the model.

Differences by productivity. The above effects are not uniform across the earnings distribution. Table 3 displays changes separately for individuals with above and below median productivity. Columns (1) and (3) show outcomes at baseline, whereas columns (2) and (4) show the counterfactual situation with 10% higher earnings in Mexico. The first two rows show that higher origin country earnings lead to shorter migrations, and more so among low-income migrants, whereas the increase in the average number of trips is slightly stronger among high-earners. Row (c) shows that changes in the fraction of migrants taking their family along are small but positive. 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 credit access, instead raise their borrowing by less (row d). See also Appendix H for model predictions under an alternative functional form for the debt limit. The last row indicates

[29]To push external validity further and raise statistical power, I use all communities surveyed by the MMP (version MMP170), even if outside the time frame of my sample restriction.

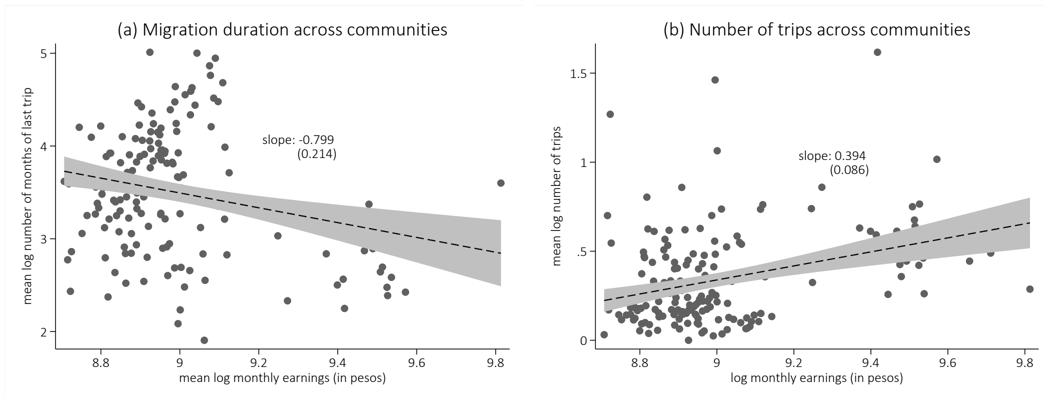

Figure 6: Model validation using empirical variation across communities. The figure plots (a) the log number of migrations, and (b) the log number of months spent in the U.S. during the most recent migration, collapsed to means within each of the 170 communities ever surveyed by the Mexican Migration Project, against the mean log monthly earnings in the same community. Dashed lines and gray areas indicate fitted linear regressions and 95% confidence intervals.

that migrants reduce their saving abroad when knowing that incomes in Mexico are higher. This reflects both a reduced urge to repatriate savings, and that within the two broad productivity groups migration becomes affordable for lower-earning individuals. Nonetheless, since with higher origin earnings return occurs at younger ages, and many of the new emigrants stay abroad only temporarily, aggregate consumption expenditure in Mexico may in fact increase, as investigated below.

The above model considers two locations, Mexico and the U.S., between which agents can migrate. By aggregating different locations within each country, the model thus abstracts from internal migration, which in particular within Mexico can be an alternative way to raise earnings for the poorer rural population. The model is too flexible to unambiguously sign the direction in which its predictions would change if internal migration was modeled explicitly. In a simpler static model, in which individuals from a rural origin can choose between (i) staying, (ii) migrating at no (or a low) financial cost to a higher income urban location in Mexico, or (iii) migrating at a high cost to the yet higher income United States, an increase in rural earnings would unambiguously shift migration away from the urban destination if there are no binding financial constraints to internal migration. The effect on migration to the U.S. still depends on the importance of financial constraint relaxation relative to the reduced incentive to leave the rural location at all, but the effect would be no smaller than if urban migration was not an option. In a dynamic model like in this paper, internal migration further may be a means to accumulate the savings needed for a later international migration. Depending on the distribution of productivity and preferences, a larger or smaller share of rural individuals may find this internal migration beneficial. Note, however, that the main counterfactual this paper focuses on is a uniform increase in earnings everywhere in Mexico, and that the data include urban individuals, who may migrate to the U.S. as well. For these higher income urban individuals, financial constraints are relatively less binding, so that the effect on emigration will be less positive—akin for what the model in this paper predicts for higher productivity agents (see also Figures 8 and 9 below).

Table 3: 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	6.03	5.21	2.54	2.37
(b) Number of migrations	1.68	1.72	2.00	2.06
(c) Share with fam. in U.S.	0.35	0.37	0.53	0.55
(d) Loan taken per trip	1073.00	1378.45	1683.33	1755.33
(e) Saving abroad per trip*	4479.15	4307.23	6372.66	6051.84

Note.— Counterfactual outcomes predicted by the model under 10% higher earnings in Mexico, separately for individuals with below and above median productivity.
* Accumulated savings abroad conditional on migrants returning.

Consumption expenditure in Mexico. A margin of migrant behavior that the above model is well-suited to address is asset accumulation. 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. 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 instead return with a stock of assets larger than what they owned before emigrating, so that domestic demand increases above and beyond the initial earnings rise. To evaluate the effect on aggregate expenditure in Mexico, I simulate the same scenario of 10% higher earnings in Mexico as before. I then compute the resulting discounted cumulative earnings increase over the life cycle, as well as the change in discounted cumulative consumption (net of migration costs) by individuals residing in Mexico. Figure 7 shows the difference between these two (as a percentage of consumption at baseline), separately for different parts of the earnings distribution. The model predicts that for the lowest earnings tercile, repatriated savings indeed make up for forgone domestic consumption by long-term emigrants, raising aggregate consumption by 15.5%—and thus by 5.5 percentage points beyond the rise in earnings. A non-targeted policy raising earnings across the board, on the other hand, would leave a slight loss to aggregate consumption in Mexico, raising it by 0.8 percentage points less than the earnings increase.

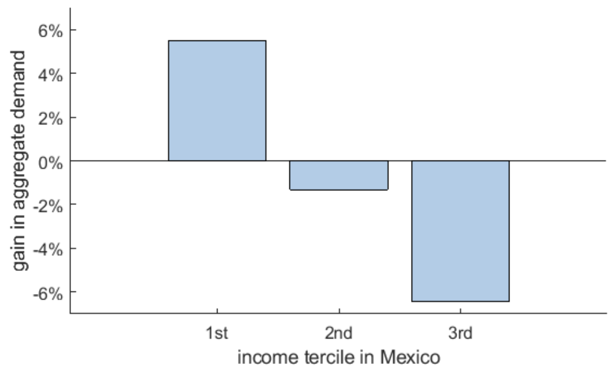

Figure 7: Effect of higher earnings on expenditure in Mexico. The figure shows the effect of 10% higher earnings in Mexico on discounted cumulative consumption (above and beyond the change in earnings and net of migration costs) along the earnings distribution. Changes are expressed as a percentage of consumption at baseline.

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, higher earnings may help overcome financial constraints to migration. On the other hand, higher earnings in the country of origin raise the opportunity cost of moving abroad. A priori, the net effect is unknown, and a disentangling of the two mechanisms requires a modeling of migration jointly with savings choices, and the use of information on both. To isolate the opportunity cost effect, I use the model to predict the changes in the fraction of individuals residing in Mexico who in any given period would find it optimal to move to the U.S. if earnings in Mexico were higher. Figure 8a 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 10% higher earnings 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 8b shows this constraint effect, revealing that for Mexicans at the very low end of the wealth distribution, the simulated rise in earnings levels by 10% is insufficient to overcome financial constraints. At intermediate wealth levels, however, the share of individuals who are constrained among those wishing to migrate is reduced, with a total average reduction by 2.7 percentage points.

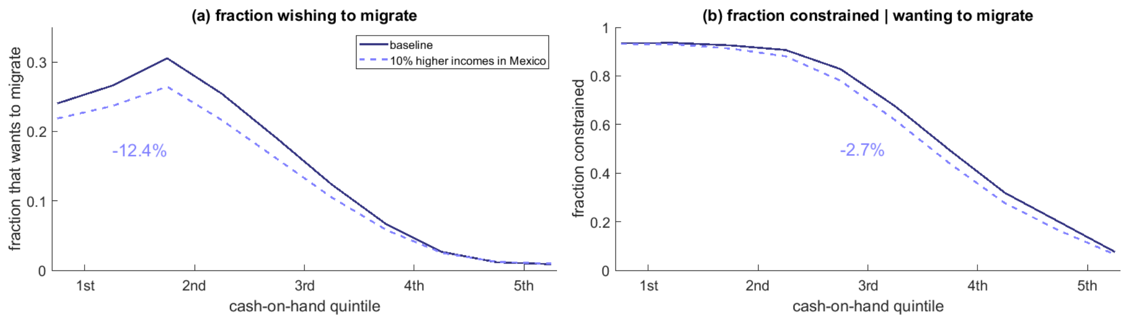

Figure 8: Constraints versus opportunity costs. The figure shows (a) the fraction of Mexican household heads who would want to move to the U.S. in a given year, and (b) the fraction among the former that faces a binding financial constraint, each along the unconditional distribution of cash-on-hand.

The net effect is shown in Figure 9a. The inverted U-shape along the wealth distribution of the effect on the fraction leaving under higher Mexican earnings is in line with recent results by Patt et al. (forthcoming), who use detailed occupational data to analyze selection in Mexican emigration. On a global level such patterns have been documented by Clemens (2014); Dustmann and Okatenko (2014), and Dao et al. (2018). The same increase in earnings raises annual return migration among migrants in the U.S. by 4.1%, which translates into the reduction in migration duration illustrated in Figure 4 above. This effect concentrates in the center and lower part of the wealth distribution (Figure 9b).

A correct assessment of migrant selection is important, not least for evaluations of the labor market impact of immigration (Llull, 2018a,b; Monras, 2020; Piyapromdee, 2021), immigrants' entrepreneurial activity (Hunt, 2011), their fiscal contribution to the host economy (Auerbach and Oreopoulos, 2000; Cascio and Lewis, 2019), as well as the adaptation of new technologies (Lewis, 2011). To illustrate the relevance of a core feature of the model for selection, the last panel of Figure 9 replicates Panel (a) for an alternative model without income dependent credit access. Specifically, it shows the distribution of emigrants if all agents had equal access to credit at the level predicted for an individual with earnings equal to the simulated population mean. Everything else equal, not accounting for tighter credit constraints at the low end of the income distribution yields a negative selection of emigrants (solid line in Figure

9c) rather than the hump-shaped pattern supported by data in many contexts. This negative selection is slightly reduced for higher origin country earnings (dashed line).

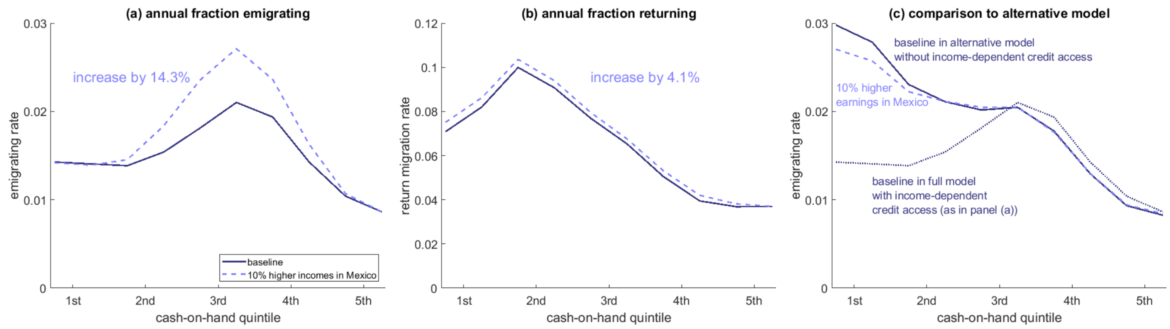

Figure 9: Emigration and return migration along the cash-on-hand distribution. The figure shows the fraction of Mexican household heads (a) emigrating to, and (b) returning from the U.S. per year along the distribution of cash-on-hand, with dashed lines indicating the change after a 10% increase in earnings in Mexico. Panel (c) compares the emigration pattern predicted by the full model, with that predicted by an alternative model in which all agents have equal access to credit.

5.4 Additional Results

The focus of this paper is on the effect of a rise in earnings levels in migrants' country of origin, a policy objective for many developing countries. Yet, the model allows a quantification also of the impact of other relevant counterfactuals. Table 4 summarizes a number of major predictions. Row (b) shows that a relaxation of borrowing constraints has qualitatively similar effects on emigration, return and repeat migration as a rise in earnings levels (row a), though quantitatively this is less pronounced. Since emigration and migration duration respond in opposite directions, column (4) lists the net effect on the share of the Mexican population that resides in the U.S. at any point in time. It shows that the effect on emigration dominates, so that the Mexican immigrant population in the U.S. slightly increases. A rise in the cost of migration (row c) or the apprehension probability for undocumented migrants (row d) lower both the emigration rate and the number of trips per migrant. Both events further raise migration duration, an effect that is line with results by Thom (2010) and Lessem (2018). An increase in earnings in the U.S. raises both the incentive to migrate and relaxes financial constraints for consecutive migrations. Hence, row (e) shows an expected positive effect on both emigration and repeat migration. For migration duration, the two mechanisms work in opposite direction: higher earnings in the U.S. reward longer stays, but the higher accumulated assets also make future re-migrations better affordable, and thus a (temporary) return to Mexico less costly. Column (3) shows that the net effect is close to zero. Finally, row (f) shows the changes in migration patterns if both in Mexico and the U.S. earnings rise by 10%. This amounts to an elimination of the opportunity cost of migration, but preserves the relaxation of financial constraints. Accordingly, the effect on both emigration and the number of trips per migrant are boosted. The faster asset accumulation abroad further induces earlier returns.

Table 4: Additional counterfactuals and their relation to migration dynamics.

	(1) emigration rate	(2) number of migrations	(3) migration duration	(4) share of Mexican population in U.S.
(a) +10% earnings in Mexico	+14.3%	+4.1%	−6.9%	+2.3%
(b) +10% in credit limit	+6.1%	+1.7%	−2.3%	+0.7%
(c) +10% migration cost	−27.6%	−12.5%	+11.6%	−10.3%
(d) +10pp apprehension probability	−5.8%	−5.6%	+4.9%	−1.2%
(e) +10% in US earnings	+13.1%	+5.1%	+0.4%	+5.9%
(f) +10% in MX&US earnings	+29.7%	+9.5%	−8.1%	+11.3%

Note.— Counterfactual outcomes as predicted by the model under (a) a 10% increase in earning in Mexico; (b) a relaxation of credit limits by 10% across all levels of income (i.e. a 10% reduction of both δ_0 and δ_y); (c) 10% higher migration cost; (d) 10 percentage point increase in apprehension probability p_A; (e) 10% higher earnings in the U.S.; and (f) higher earnings in both Mexico and in the U.S. Numbers indicate behavioral changes net of composition effects as described in the text above.

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 short-term effect on emigration, but also on the more dynamic dimensions of migration duration and the propensity to move repeatedly, as well as other choices such as saving behavior. Each of these depends on the prevalence of financial constraints and whether agents can borrow in order to finance a migration.

I find 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. Understanding the mechanism behind any measured net effect is important for an appreciation of growth enhancing policies in low and middle-income countries and their longer-term implications for the extent and permanence of migrations. The results show that for poor individuals higher earnings lead to a more than proportional increase in domestic consumption expenditure, financed by repatriated savings of new migrants who are more likely to return. My results further show that a careful modeling of credit access is key, both for the estimation of important structural parameters and for counterfactual predictions of the model. 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.

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Online Appendix

A Additional Detail on Data and Descriptives

A.1 Mexican Migration Project

The Mexican Migration Project[30] is a household-level survey, administered in several samples of Mexican communities over time. The main analysis restricts the sample to the years 1996-2007, excludes individuals who were born in the U.S. and focuses on male household heads aged 16-64 without tertiary education. The estimation does, however, use information on migrations of spouses to identify model parameters relating to dependent family members' location choice. The MMP is representative within the communities surveyed, whereas these communities are a non-random selection within Mexico. See Section 4.2 of the paper for how this is addressed in the estimation.

To illustrate the prevalence of repeat migration, Figure A1a 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. Figure A1b shows the distribution of duration of the most recent migration. The last panel of Figure A1 shows the variation in emigration rates over individuals' life cycle.

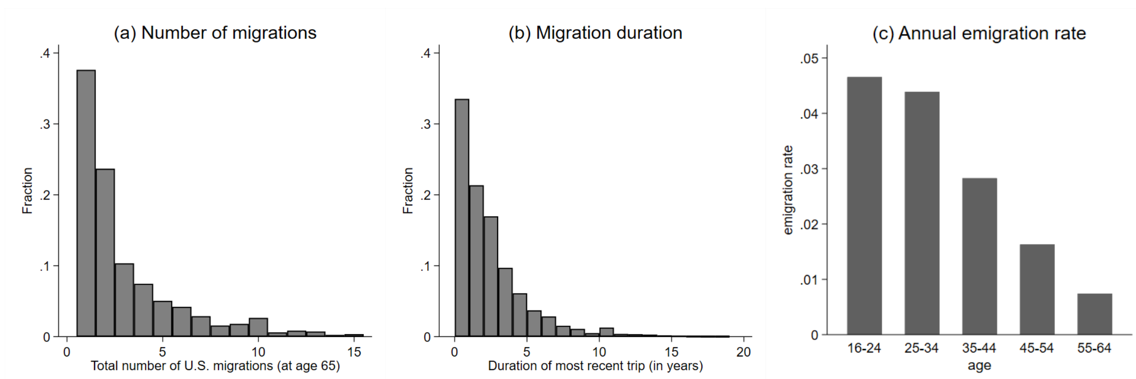

Figure A1: Number of migrations and migration durations. Figure A1a shows the distribution of the number of migrations made per returned migrant by age 65. The distribution is based on the MMP cross-sectional files, restricting the sample to Mexican-born non-tertiary educated males aged 65 or older at the time of the survey. Figure A1b, 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. Figure A1c shows annual emigration rates over the life cycle. Source: MMP 143.

[30]See mmp.opr.princeton.edu. The version used in this paper is the MMP143, except for the external validity check of Figure 6, which uses the MMP170.

A.2 Mexican Family Life Survey

The Mexican Family Life Survey[31] is a nationally representative data set, of which I use the 2002 and 2005 waves. In addition to longitudinal information, including on earnings, the MxFLS reports whether and for how long individuals have been to the U.S., and contains detailed information on assets and debt.

Figure A2a, which plots mean residuals of (log) debt against deciles of (log) earnings residuals, confirms the same positive relation between debt and earnings conditional on age, education, family status and year of observation. Panel b of the figure shows the distributions of log assets in 2002 (conditional on age, education, family status, weeks and hours worked) among individuals who have never been to the U.S., separately for those who by 2005 have migrated and those who have not.

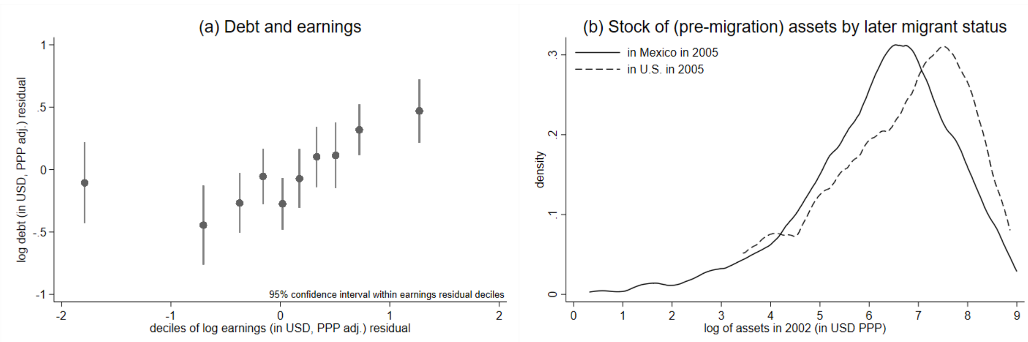

Figure A2: Assets and debt. The figure shows (a) mean log debt (calculated as negative net assets, in PPP adjusted USD) by earnings deciles (residuals net of age, education, family status, weeks and hours worked, and year of observation); and (b) distributions of log assets in 2002 (conditional on age, education, family status, weeks and hours worked) among individuals who have never been to the U.S., separately for those who by 2005 have migrated and those who have not. Source: MxFLS, 2002, 2005.

A.3 Survey of Income and Program Participation

As a U.S. source suitable to analyse long-term migrants, I use the Survey of Income and Program Participation[32], which provides large enough samples for a separate analysis of Mexicans. In line with the restriction of the MMP sample, I use the three SIPP panels 1996-2001, 2001-2004 and 2004-2007. The SIPP provides monthly information, which allows an investigation into the importance of seasonality for Mexican employment in the U.S. Figure A3a shows the monthly employment rate of Mexicans observed in the SIPP. Labor demand is more (less) seasonal than the pattern observed

[31] See `ennvih-mxfls.org`, and in particular Rubalcava, Luis and Teruel, Graciela (2006), "Mexican Family Life Survey, Second Round", Working Paper.

[32] See `census.gov/programs-surveys/sipp.html`.

in Figure A3a if it is accompanied by pro-cyclical (counter-cyclical) variation in labor supply.

U.S. Border Patrol data on monthly apprehensions in Figure A3a point towards migration being pro-cyclical, with an about twice as high number of apprehensions at the U.S. southern border during the summer months than in winter. Note that seasonality in the scale of migration or in the size of the Mexican workforce in the U.S. alone may derive from either demand or supply factors. The seasonal variation in employment *rates* together with the parallel variation in immigration, however, is a strong indication of at least some degree of seasonality in the *demand* for Mexican labor in the U.S.

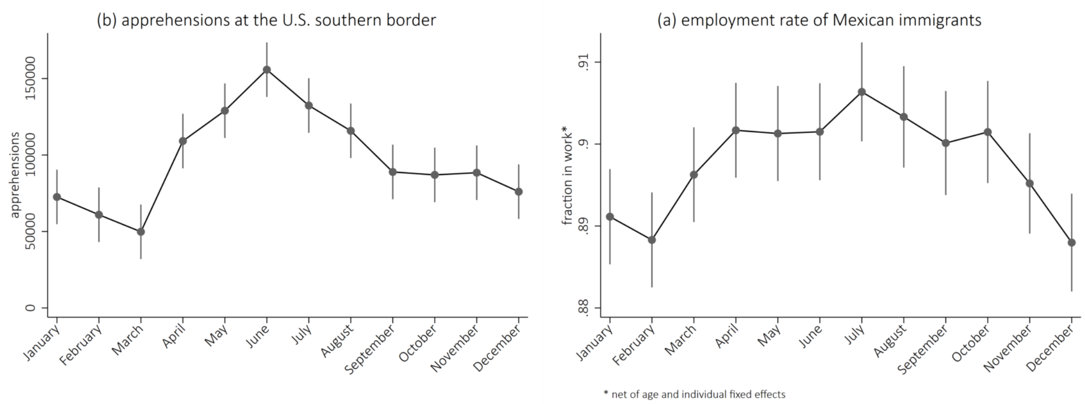

Figure A3: Seasonality. The graphs show seasonality in (a) average monthly apprehensions at the U.S. southern border, and (b) the share among non-tertiary educated Mexican-born male household heads aged 16-64 residing in the U.S. who worked for at least one week during the respective month. Vertical lines show 95% confidence intervals. Sources: (a) U.S. Border Patrol, 1999-2007; (b) SIPP, 1996-2007.

A.4 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. Eligibility of families within the randomized communities was determined by a pre-program survey in 1997, based on a multi-dimensional marginalization measure.[33] 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. For children up to the age of 14, school attendance in control communities was 97%

[33]For details, see Skoufias, E., Davis, B., and Behrman, J. ("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, 1999.).

in 1998. Hence, for families with children in that age group, the transfer was in fact unconditional. For the estimation, I thus restrict the sample to these families. To evaluate the program, household data in both this treatment group and in a control group of 186 communities were collected.[34]

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 A1 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. ("Randomness in the Experimental Samples of Progresa (Education, Health, and Nutrition Program)." International Food Policy Research Institute, Washington, DC, 1999.) for an extensive evaluation of the Progresa randomization.

Table A1: 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.

[34]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.)

B Model Specification

This appendix details the specification of components of the model presented in Section 3, in particular the timing, functional form assumptions, and the sources for externally set parameters.

Within-period timing.

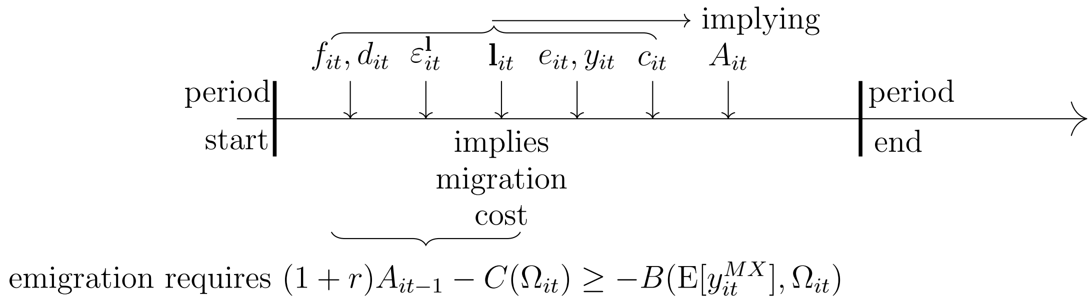

Figure A4: Assumed timing within each period in the model.

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

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

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

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

and

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

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

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

and

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

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.[35] Retirement schemes in Mexico and in the U.S. are approximated based on OECD[36] 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% (55.3% 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, $X^{US}/(65-16)$. Undocumented migrants in the U.S. receive only the Mexican share of retirement benefits.

Borrowing limit. Households with a working age head can take up credit. They face two constraints to the maximum amount of debt, $B(\mathrm{E}[y^{MX}_{it}], \Omega_{it})$, they can hold: The first constraint depends on expected retirement benefits, and becomes tighter with age, ensuring full debt repayment. Family and social networks in Mexico make this a plausible assumption. 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 $a_{it} < a^{ret}$,

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

The first argument of the minimum function captures the estimated income dependent part, the second argument ensures debt repayment before the end of life.

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 $1/(1+r)$.

Relative price level. Monetary values, including earnings are expressed in purchasing power adjusted U.S. dollars throughout the paper. To account for different price levels, the stock of assets is adjusted when agents migrate. Based on purchasing power parities from the OECD and consumer price indices for actual individual consumption from the World Bank's (2015) World Development Indicators, the mean relative price level during 1996-2007 between the U.S. and Mexico was 1.639. I use this factor to adjust assets in the model at the time of migration.

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

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

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,

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

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 overall cost is given by

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

Apprehension probability. Attempted migrations from Mexico to the U.S. by undocumented migrants fail with probability $p_a(\Omega_{it}|d_{it} = 0) = 0.2246$, based on annual apprehension probabilities reported by the Mexican Migration Project.

C Assumptions on Credit Constraints and the Estimation 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 $B = 0$ (i.e. borrowing is ruled out) 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.[37] Figure A5 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 5,760 USD, the criterion under the restricted model attains its minimum at about 4,000 USD. 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.

[37]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.

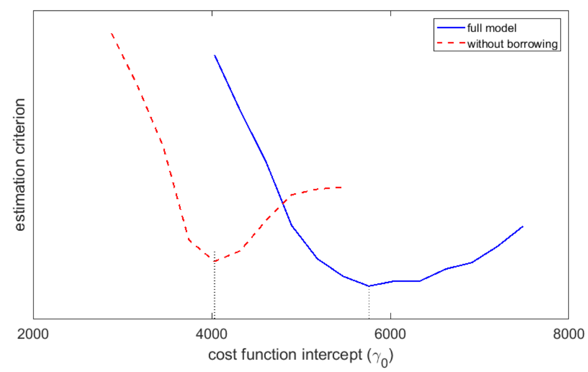

Figure A5: Estimation bias in the absence of borrowing. The figure plots the moment criterion minimized by the indirect inference estimator against different values for the intercept parameter γ_0 of the migration cost function $C(\Omega)$, separately for the full model of Section 3 (solid line), and 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.

D Approximation and Identification of Unobserved Heterogeneity

The simulation approximates unobserved heterogeneity by a finite mixture, assuming a discrete number of types of agents, 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 regressions of earnings on age and U.S. experience. Time spent in the U.S. helps to identify the marginal distribution of preferences π_i^{US} for being abroad. 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.

The estimation further allows for different distributions of unobserved characteristics in the two non-representative samples used in the estimation (the MMP and Progresa). Let τ index the T discrete types of simulated individuals used to approximate 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. For these representative samples, types are weighted equally, so that no weights need to be estimated. 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 different 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.

In the absence of data that provide longitudinal information on both sides of the border for the same individual, identification requires the assumption that the ranking of types with respect to their productivity in Mexico and their productivity in the United States is preserved. This assumption for instance implies (but is stronger than) a positive correlation between these dimensions. Like any discretization, the approximation of unobserved heterogeneity by a finite number of discrete types introduces an error which may constrain the values that some higher order moments of the distribution of unobserved characteristics can take when simulated from the model. In particular, the lowest value which the correlation between productivity in Mexico and productivity in the U.S. can take while preserving the ranking assumption is $1/(T-1)$, where T is the number of types.[38] While $1/(T-1)$ decreases for larger numbers of types, it does not vanish for computationally feasible numbers. This has implications also for the correlations with the third dimension of unobserved heterogeneity, that is, for the values which $\text{corr}(\alpha^{MX}, \pi^{US})$ and $\text{corr}(\alpha^{US}, \pi^{US})$ can take. In what follows, I derive these restrictions and identify the set of values for these correlations that the model cannot generate.

Regardless of the ranking assumption, correlations ρ_{xy}, ρ_{xz} and ρ_{yz} between three random variables x, y and z are constrained by the relations

$$\begin{aligned}\rho_{yz} &\geq \rho_{xy} \cdot \rho_{xz} - \sqrt{(1-\rho_{xy}^2)(1-\rho_{xz}^2)} \\ \rho_{yz} &\leq \rho_{xy} \cdot \rho_{xz} + \sqrt{(1-\rho_{xy}^2)(1-\rho_{xz}^2)}.\end{aligned}$$

To arrive at these inequalities, recall that the correlation matrix $\begin{bmatrix} 1 & \rho_{xy} & \rho_{xz} \\ \rho_{xy} & 1 & \rho_{yz} \\ \rho_{xz} & \rho_{yz} & 1 \end{bmatrix}$ is positive semi-definite, and hence

$$1 - \rho_{yz}^2 - \rho_{xy}(\rho_{xy} - \rho_{xz}\rho_{yz}) + \rho_{xz}(\rho_{xy}\rho_{yz} - \rho_{xz}) \geq 0$$

Add $\rho_{xy}^2\rho_{xz}^2$ and re-arrange to get

$$\left(1-\rho_{xy}^2\right)\left(1-\rho_{xz}^2\right) \geq \left(\rho_{xy}\rho_{xz} - \rho_{yz}\right)^2.$$

[38] Note that when both productivity dimensions are ranked equally across types, a covariance of zero would require at least one dimension to collapse to a single point, in which case the variance would be zero and the correlation would not be defined.

Taking the square root yields two cases:

1. If $\rho_{yz} \leq \rho_{xy}\rho_{xz}$,

$$\sqrt{\left(1-\rho_{xy}^2\right)\left(1-\rho_{xz}^2\right)} \geq \rho_{xy}\rho_{xz} - \rho_{yz}$$

   or

$$\rho_{yz} \geq \rho_{xy}\rho_{xz} - \sqrt{\left(1-\rho_{xy}^2\right)\left(1-\rho_{xz}^2\right)}. \tag{3}$$

2. If $\rho_{yz} \geq \rho_{xy}\rho_{xz}$,

$$-\sqrt{\left(1-\rho_{xy}^2\right)\left(1-\rho_{xz}^2\right)} \leq \rho_{xy}\rho_{xz} - \rho_{yz}$$

   or

$$\rho_{yz} \leq \rho_{xy}\rho_{xz} + \sqrt{\left(1-\rho_{xy}^2\right)\left(1-\rho_{xz}^2\right)}. \tag{4}$$

(3) and (4) determine the combinations for the correlations between x, y and z that are theoretically possible, regardless any assumptions in the model of Section 3.

To apply these constraints to the model, replace $x = \alpha^{MX}$, $y = \alpha^{US}$ and $z = \pi^{US}$. The left panel of Figure A6 shows the theoretically permissible combinations of $\text{corr}(\alpha^{MX}, \pi^{US})$ and $\text{corr}(\alpha^{US}, \pi^{US})$ for different values of $\text{corr}(\alpha^{MX}, \alpha^{US})$. The smallest possible value for $\text{corr}(\alpha^{MX}, \alpha^{US})$ when there are $T = 4$ types, and the ranking of α^{MX} equals the ranking of α^{US}, is $1/(T-1) = 1/3$.[39] The possible combinations of $\text{corr}(\alpha^{MX}, \pi^{US})$ and $\text{corr}(\alpha^{US}, \pi^{US})$ in that case are indicated by the blue ellipse in the graph. For higher correlations between productivity in Mexico and in the U.S., $\text{corr}(\alpha^{MX}, \pi^{US})$ and $\text{corr}(\alpha^{US}, \pi^{US})$ must be closer to each other (as in the green and yellow ellipses). The relatively small red shaded area indicates the combinations of $\text{corr}(\alpha^{MX}, \pi^{US})$ and $\text{corr}(\alpha^{US}, \pi^{US})$ that would be permissible under the ranking assumption, but cannot be generated by the model when there are only four types. Any combinations outside the dashed red line cannot be generated regardless of the assumption in my model or the number of types used to approximate unobserved heterogeneity.

As a numerical counterpart, panel (b) of the figure displays the correlations computed for 1 million random triples of 4-element vectors, with two dimensions of each triplet being sorted. Color shading indicates the values of $\text{corr}(\alpha^{MX}, \alpha^{US})$. The graph confirms that with four types the theoretical range of correlation combinations derived above can indeed be covered.

[39] A simple example for this would be two vectors [0 0 0 1] and [0 1 1 1].

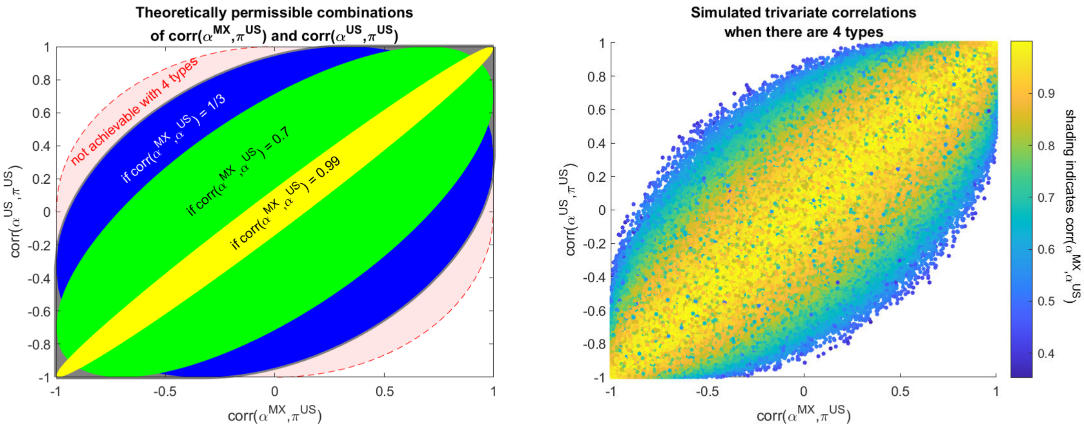

Figure A6: Discretization and feasible correlations. The figure displays combinations of correlations between three dimensions of unobserved heterogeneity. Panel (a) shows all possible combinations of correlations when two dimensions of unobserved heterogeneity are sorted. The red shaded area shows combinations that are theoretically possible, but cannot be generated under an approximation with four types. Panel (b) shows as a numerical counterpart the correlations computed for 1 million random triples of 4-element vectors (in this example drawn from uniform distributions), with two dimensions of each triplet being sorted. Color shading indicates the values of corr$(\alpha^{MX}, \alpha^{US})$, whereas corr$(\alpha^{MX}, \pi^{US})$ and corr(α^{US}, π^{US}) are shown along the axes.

E 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. Although the derivation is straight forward, I have not actually seen it spelled out. Hence this additional appendix section.[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

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

[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 Kenneth J. Singleton ("Empirical Dynamic Asset Pricing: Model Specification and Econometric Assessment." Princeton University Press, 2006.) of GMM estimation with time series data of unequal length.

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 each data set ς used increases 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^s_ς increase at a rate such that

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

with $0 < n^s_\varsigma < \infty$.

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

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

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

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

F 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 A2 lists the model parameters to be estimated and the identifying moments more systematically.

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 A7 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. The key 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

$$loan_i = \alpha_0 + \alpha_1 \mathbb{1}_i^{treated} + \boldsymbol{\alpha_2}'\mathbf{x}_i + u_i, \tag{5}$$

where $\mathbf{x}_i$ controls for a number of household characteristics. In this sample of fairly

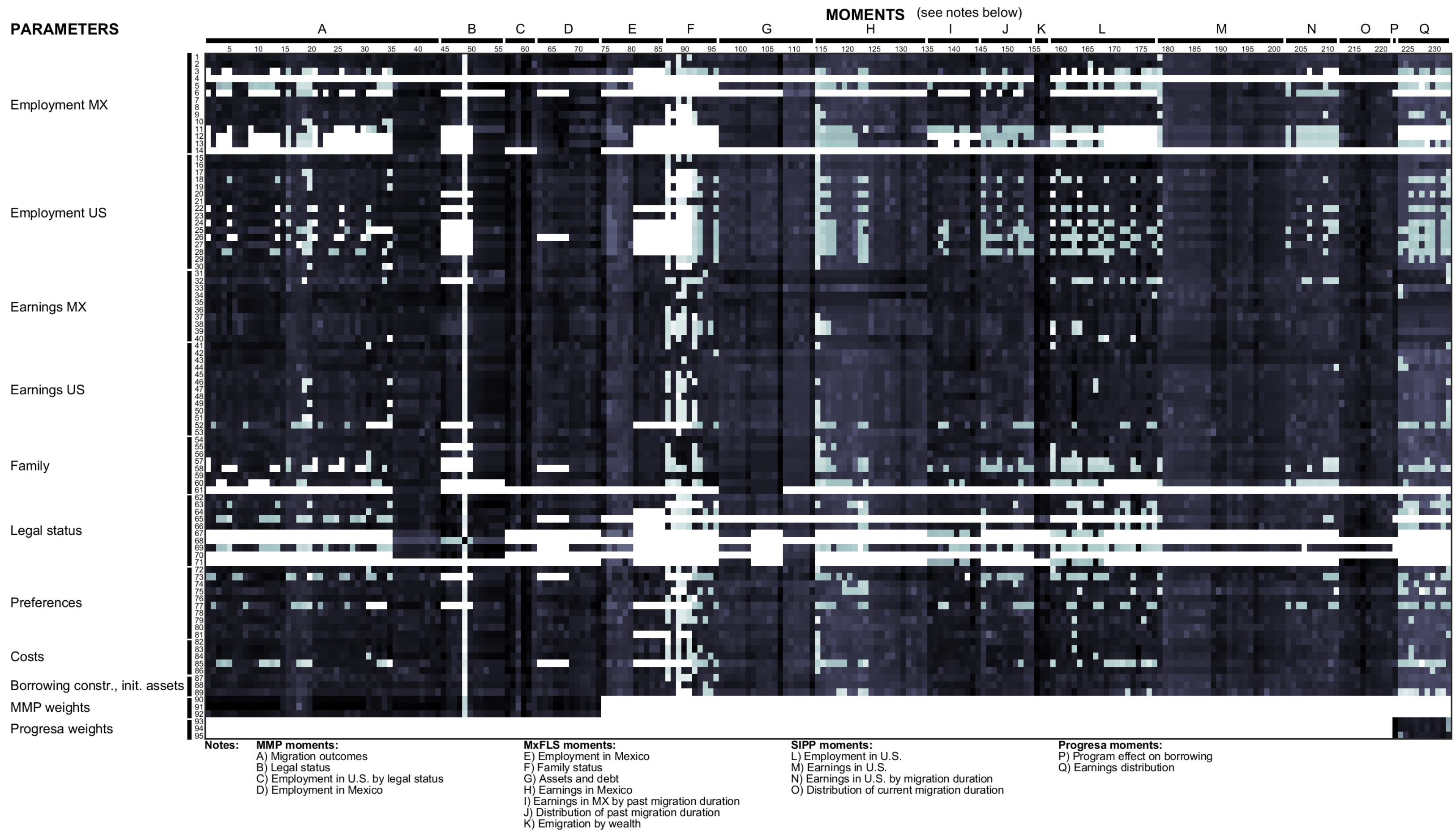

Figure A7: Mapping of moments into parameters. The figure illustrates the gradient matrix of moments used for identification with respect to model parameters. Darker shades indicate a stronger sensitivity of moments to changes in parameters. Moments are computed for a simulated sample of 40,000 agents.

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
$\phi_c, \phi_A, \tilde{\alpha}_A$	asset level at different ages	MxFLS
$\phi_f^{\mathbf{l}}$	family location by age, and stock of assets/debt by family status	MxFLS, MMP
$\sigma^{\varepsilon}(a)$	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 A2: Identification of model parameters

poor households, the mean monthly transfer amount of 260.32 pesos (51.14 PPP adjusted USD) corresponds to 27.8% 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 A3 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.4 provides additional details, including pre-program differences across communities.

Table A3: Average treatment effect of the program on loans taken within 6 months.

	(1)	(2)
	loan>0	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: log of 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.

After introducing treatment status as an additional state variable, the treatment effect in Table A3 is a moment the model can generate, and that is included in the structural estimation.[41] Indirect inference estimation does not actually require consistency of $\hat{\alpha}_1$, as (5) only serves as an auxiliary regression. The importance rather lies with the income variation being unrelated to location preferences π_i^{US}.

Figure A8 shows the contribution of this moment to the estimation criterion , and thus to identification of the slope parameter δ_y. The figure 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 reason the minimum is slightly to the left of the estimate of δ_y derives from the fact that other moments, namely the incidence and level of debt in the Mexican Family Life Survey also contribute to identification of this parameter and the model is over-identified.

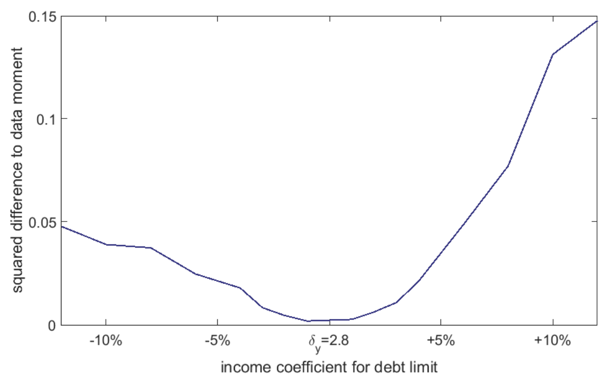

Figure A8: Credit access and the ATE of Progresa. The figure plots the contribution of the estimated treatment effect of Progresa on borrowing to the estimation criterion minimized by the indirect inference estimator against different values for the structural effect δ_y of income on the debt limit. Specifically, it shows the squared difference between the observed and simulated moment for different values δ_y.

To illustrate the contribution of other moments to the identification of δ_y, Figure A9 shows the sensitivity measure proposed by Andrews et al. (2017) for this parameter. This sensitivity matrix, $\left(\frac{\partial D'}{\partial \vartheta}\Big|_{\hat{\theta}} W \frac{\partial D}{\partial \vartheta'}\Big|_{\hat{\theta}}\right)^{-1} \frac{\partial D'}{\partial \vartheta}\Big|_{\hat{\theta}} W$, is inversely related to the gradient of moments with respect to parameters. To summarize the sensitivity matrix, the figure indicates the mean sensitivity within groups of moments used in the estimation. As suggested by Andrews et al. (2017) for better comparability, sensitivity is scaled by the standard deviation of each moments. The figure shows that the estimate of credit access primarily is sensitive also to the more precisely measured fraction of households holding debt and its level.

Figure A10 summarizes the fit for all 233 moments targeted in the estimation.

[41] Note that any source of variation requires an additional state variable, which for instruments like rainfall would need to be continuous, considerably contributing to the computational burden.

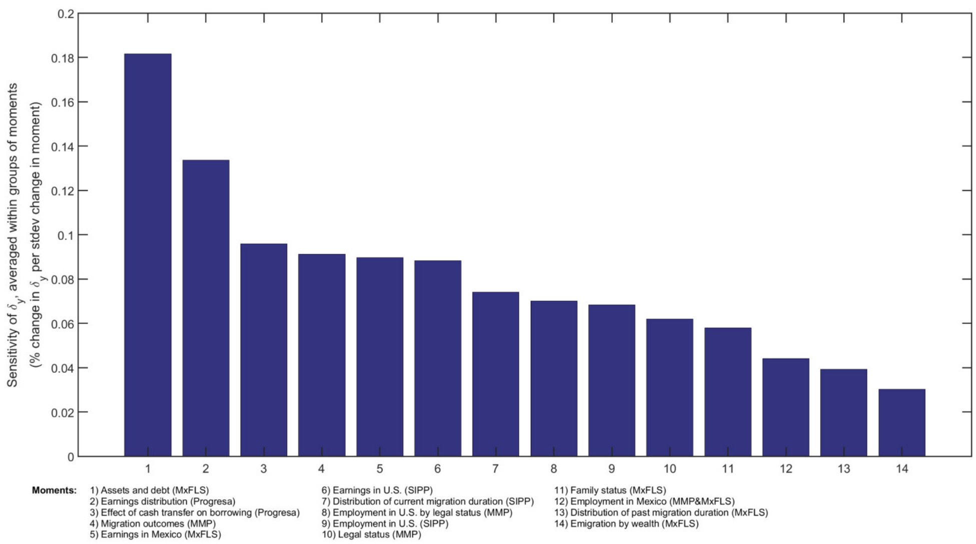

Figure A9: Sensitivity of δ_y to moments values. The figure shows the sensitivity measure proposed by Andrews et al. (2017) for the structural effect δ_y of income on the debt limit. Bars indicate the mean sensitivity within groups of moments used in the estimation. For better comparability, sensitivity is scaled by the standard deviation of moments, as suggested by Andrews et al. (2017).

It compares observed data moments (expressed in terms of their standard deviation) on the horizontal axis to the corresponding moments simulated from the model. Tables A4-A11 list the individual moments used in the estimation together with their simulated counterparts and standard deviations.

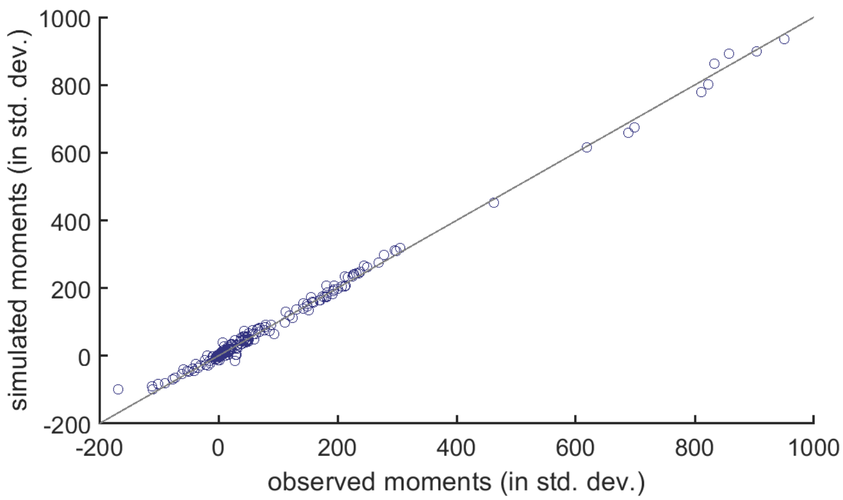

Figure A10: Model fit: Simulated vs observed data moments, each expressed in terms of the empirical standard deviation of the respective moment. Model predictions are based on 40,000 simulated agents.

Table A4: 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)	0.523
$\mathbb{1}[25 \leq age < 35]$	0.553	(0.077)	0.648
$\mathbb{1}[35 \leq age < 45]$	0.372	(0.072)	0.393
$\mathbb{1}[45 \leq age < 55]$	0.269	(0.066)	0.114
$\mathbb{1}[55 \leq age < 65]$	0.283	(0.061)	0.314
Transition to not having family (MxFLS):			
$\mathbb{1}[16 \leq age < 25]$	0.053	(0.024)	0.075
$\mathbb{1}[25 \leq age < 35]$	0.007	(0.005)	0.007
$\mathbb{1}[35 \leq age < 45]$	0.013	(0.004)	0.008
$\mathbb{1}[45 \leq age < 55]$	0.026	(0.004)	0.030
$\mathbb{1}[55 \leq age < 65]$	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)	0.028
$\mathbb{1}[25 \leq age < 35]$	0.284	(0.022)	0.351
$\mathbb{1}[35 \leq age < 45]$	0.433	(0.023)	0.577
$\mathbb{1}[45 \leq age < 55]$	0.526	(0.023)	0.450
$\mathbb{1}[55 \leq age < 65]$	0.514	(0.024)	0.500
$\mathbb{1}[working]$	0.369	(0.022)	0.283
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)	0.003
$\mathbb{1}[55 \leq age < 65]$	0.002	(0.014)	0.003
$\mathbb{1}[working]$	−0.002	(0.009)	−0.003

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

Table A5: Employment in Mexico.

Moment	Data	Standard error	Simulation
Regression of transition into work in Mexico (MMP) on:			
$\mathbb{1}[16 \leq age < 25]$	0.459	(0.016)	0.744
$\mathbb{1}[25 \leq age < 35]$	0.329	(0.047)	0.347
$\mathbb{1}[35 \leq age < 45]$	0.095	(0.039)	0.125
$\mathbb{1}[45 \leq age < 55]$	0.024	(0.031)	0.019
$\mathbb{1}[55 \leq age < 65]$	0.033	(0.025)	0.018
$\mathbb{1}[been\ in\ U.S.]$	−0.002	(0.043)	−0.049
Regression of transition out of work in Mexico (MMP) 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)	−0.000
Regression of working in Mexico (MxFLS) on:			
$\mathbb{1}[16 \leq age < 25]$	0.946	(0.020)	0.961
$\mathbb{1}[25 \leq age < 35]$	0.956	(0.015)	0.973
$\mathbb{1}[35 \leq age < 45]$	0.948	(0.015)	0.978
$\mathbb{1}[45 \leq age < 55]$	0.898	(0.015)	0.968
$\mathbb{1}[55 \leq age < 65]$	0.770	(0.016)	0.920
$\mathbb{1}[summer]$	−0.018	(0.014)	−0.001
Regression of season last worked in Mexico (MxFLS) on:			
$\mathbb{1}[16 \leq age < 25]$	0.689	(0.208)	0.586
$\mathbb{1}[25 \leq age < 35]$	0.660	(0.195)	0.609
$\mathbb{1}[35 \leq age < 45]$	0.770	(0.207)	0.617
$\mathbb{1}[45 \leq age < 55]$	0.882	(0.190)	0.596
$\mathbb{1}[55 \leq age < 65]$	0.769	(0.190)	0.708
$\mathbb{1}[summer]$	−0.637	(0.185)	−0.124

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

Table A6: 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)	0.611
$\mathbb{1}[25 \leq age < 35 \cap winter]$	0.500	(0.048)	0.447
$\mathbb{1}[35 \leq age < 45 \cap winter]$	0.308	(0.052)	0.218
$\mathbb{1}[45 \leq age < 55 \cap winter]$	0.145	(0.044)	0.062
$\mathbb{1}[55 \leq age < 65 \cap winter]$	0.034	(0.035)	0.004
$\mathbb{1}[16 \leq age < 25 \cap summer]$	0.000	(0.145)	0.434
$\mathbb{1}[25 \leq age < 35 \cap summer]$	0.157	(0.046)	0.270
$\mathbb{1}[35 \leq age < 45 \cap summer]$	0.152	(0.048)	0.111
$\mathbb{1}[45 \leq age < 55 \cap summer]$	0.075	(0.036)	0.021
$\mathbb{1}[55 \leq age < 65 \cap summer]$	0.052	(0.030)	0.001
Regression of transition out of work in the U.S. (SIPP) on:			
$\mathbb{1}[16 \leq age < 25 \cap winter]$	0.023	(0.013)	0.008
$\mathbb{1}[25 \leq age < 35 \cap winter]$	0.023	(0.004)	0.013
$\mathbb{1}[35 \leq age < 45 \cap winter]$	0.023	(0.004)	0.012
$\mathbb{1}[45 \leq age < 55 \cap winter]$	0.022	(0.005)	0.013
$\mathbb{1}[55 \leq age < 65 \cap winter]$	0.085	(0.008)	0.072
$\mathbb{1}[16 \leq age < 25 \cap summer]$	0.005	(0.009)	0.002
$\mathbb{1}[25 \leq age < 35 \cap summer]$	0.004	(0.003)	0.001
$\mathbb{1}[35 \leq age < 45 \cap summer]$	0.004	(0.003)	0.001
$\mathbb{1}[45 \leq age < 55 \cap summer]$	0.008	(0.004)	0.002
$\mathbb{1}[55 \leq age < 65 \cap summer]$	0.009	(0.008)	0.017
Regression of working in the U.S. (MMP) on:			
$\mathbb{1}[legal]$	-0.003	(0.013)	-0.023
U.S. experience	0.001	(0.001)	-0.003
constant	0.886	(0.007)	0.882
Regression of fraction of year worked in the U.S. (MMP) on:			
$\mathbb{1}[legal]$	-0.186	(0.010)	0.011
U.S. experience	0.011	(0.001)	0.001
constant	0.855	(0.006)	0.756

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

Table A7: Earnings and Assets.

Moment	Data	Standard error	Simulation
Regression of log annual earnings in Mexico (MxFLS) on:			
$\mathbb{1}[16 \le age \le 20]$	7.885	(0.090)	8.164
$\mathbb{1}[20 < age \le 25]$	8.307	(0.043)	8.390
$\mathbb{1}[25 < age \le 30]$	8.333	(0.031)	8.524
$\mathbb{1}[30 < age \le 35]$	8.347	(0.028)	8.644
$\mathbb{1}[35 < age \le 40]$	8.340	(0.027)	8.713
$\mathbb{1}[40 < age \le 45]$	8.317	(0.028)	8.759
$\mathbb{1}[45 < age \le 50]$	8.226	(0.030)	8.799
$\mathbb{1}[50 < age \le 55]$	8.120	(0.033)	8.840
$\mathbb{1}[55 < age \le 60]$	8.026	(0.038)	8.851
$\mathbb{1}[60 < age < 65]$	7.901	(0.051)	8.850
standard deviation of residual	0.946	(0.016)	0.755
Regression of log annual earnings in the U.S. (SIPP) on:			
$\mathbb{1}[16 \le age \le 20]$	8.915	(0.116)	8.722
$\mathbb{1}[20 < age \le 25]$	9.418	(0.049)	8.944
$\mathbb{1}[25 < age \le 30]$	9.457	(0.045)	9.084
$\mathbb{1}[30 < age \le 35]$	9.547	(0.045)	9.234
$\mathbb{1}[35 < age \le 40]$	9.468	(0.047)	9.356
$\mathbb{1}[40 < age \le 45]$	9.490	(0.049)	9.399
$\mathbb{1}[45 < age \le 50]$	9.554	(0.054)	9.508
$\mathbb{1}[50 < age \le 55]$	9.398	(0.060)	9.563
$\mathbb{1}[55 < age \le 60]$	9.270	(0.071)	9.638
$\mathbb{1}[60 < age < 65]$	8.914	(0.114)	9.548
$\mathbb{1}[5 \le \textit{U.S. experience} < 10]$	0.181	(0.046)	0.229
$\mathbb{1}[10 \le \textit{U.S. experience} < 15]$	0.304	(0.047)	0.317
$\mathbb{1}[15 \le \textit{U.S. experience}]$	0.477	(0.043)	0.361
standard deviation of residual	0.703	(0.016)	0.911
Regression of having positive net assets (MxFLS) on:			
$\mathbb{1}[16 \le age < 25]$	0.848	(0.023)	1.025
$\mathbb{1}[25 \le age < 35]$	0.817	(0.019)	0.887
$\mathbb{1}[35 \le age < 45]$	0.841	(0.018)	0.720
$\mathbb{1}[45 \le age < 55]$	0.874	(0.018)	0.786
$\mathbb{1}[55 \le age < 65]$	0.940	(0.018)	0.907
$\mathbb{1}[family]$	−0.076	(0.017)	−0.080
Regression of log debt (MxFLS) on:			
$\mathbb{1}[16 \le age < 25]$	4.293	(0.245)	7.150
$\mathbb{1}[25 \le age < 35]$	4.666	(0.217)	7.165
$\mathbb{1}[35 \le age < 45]$	4.921	(0.215)	7.280
$\mathbb{1}[45 \le age < 55]$	4.684	(0.215)	7.298
$\mathbb{1}[55 \le age < 65]$	4.634	(0.228)	7.621
$\mathbb{1}[family]$	−0.346	(0.209)	−0.074
Regression of log positive assets (MxFLS) on:			
$\mathbb{1}[16 \le age < 25]$	5.638	(0.149)	7.970
$\mathbb{1}[25 \le age < 35]$	6.201	(0.109)	8.233
$\mathbb{1}[35 \le age < 45]$	6.893	(0.106)	8.352
$\mathbb{1}[45 \le age < 55]$	7.087	(0.106)	8.414
$\mathbb{1}[55 \le age < 65]$	7.252	(0.104)	8.527
$\mathbb{1}[family]$	−0.091	(0.098)	−0.087

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

Table A8: 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)	0.290
number of trips at $25 \leq age < 35$	0.513	(0.011)	0.487
number of trips at $35 \leq age < 45$	0.536	(0.011)	0.532
number of trips at $45 \leq age < 55$	0.482	(0.012)	0.531
number of trips at $55 \leq age < 65$	0.587	(0.015)	0.526
U.S. experience at $16 \leq age < 25$	0.382	(0.028)	0.468
U.S. experience at $25 \leq age < 35$	0.866	(0.019)	0.990
U.S. experience at $35 \leq age < 45$	0.955	(0.019)	1.223
U.S. experience at $45 \leq age < 55$	0.877	(0.021)	1.233
U.S. experience at $55 \leq age < 65$	0.977	(0.027)	1.153
share in U.S. at $16 \leq age < 25$	0.091	(0.002)	0.082
share in U.S. at $25 \leq age < 35$	0.075	(0.002)	0.065
share in U.S. at $35 \leq age < 45$	0.047	(0.002)	0.037
share in U.S. at $45 \leq age < 55$	0.030	(0.002)	0.028
share in U.S. at $55 \leq age < 65$	0.014	(0.002)	0.013
share of year in U.S. at $16 \leq age < 25$	0.906	(0.008)	0.800
share of year in U.S. at $25 \leq age < 35$	0.855	(0.006)	0.931
share of year in U.S. at $35 \leq age < 45$	0.847	(0.007)	0.974
share of year in U.S. at $45 \leq age < 55$	0.850	(0.011)	0.972
share of year in U.S. at $55 \leq age < 65$	0.846	(0.020)	0.886
share with family in U.S. at $16 \leq age < 25$	0.184	(0.016)	0.025
share with family in U.S. at $25 \leq age < 35$	0.099	(0.009)	0.163
share with family in U.S. at $35 \leq age < 45$	0.077	(0.010)	0.404
share with family in U.S. at $45 \leq age < 55$	0.135	(0.015)	0.415
share with family in U.S. at $55 \leq age < 65$	0.162	(0.027)	0.329
Regression of migrating to the U.S. (MxFLS) on:			
$A_{it}/1e6$	1.046	(1.087)	−0.019
$\mathbb{1}[family]$	0.011	(0.009)	−0.005
$\mathbb{1}[been\ to\ the\ U.S.]$	0.034	(0.008)	0.003
Regression of migrating to the U.S. (MMP) on:			
$\mathbb{1}[16 \leq age < 25]$	0.082	(0.006)	0.060
$\mathbb{1}[25 \leq age < 35]$	0.068	(0.006)	0.040
$\mathbb{1}[35 \leq age < 45]$	0.054	(0.006)	0.034
$\mathbb{1}[45 \leq age < 55]$	0.044	(0.006)	0.032
$\mathbb{1}[55 \leq age < 65]$	0.029	(0.006)	0.032
$\mathbb{1}[family]$	−0.050	(0.006)	−0.012
$\mathbb{1}[works]$	0.006	(0.003)	−0.032
$\mathbb{1}[been\ to\ the\ U.S.]$	0.053	(0.002)	0.006
$\mathbb{1}[legal]$	0.095	(0.003)	0.009

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

Table A9: 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)	−0.668
3. dec	−0.417	(0.010)	−0.466
4. dec	−0.186	(0.010)	−0.299
5. dec	−0.000	(0.010)	−0.141
6. dec	0.173	(0.010)	0.029
7. dec	0.335	(0.010)	0.221
8. dec	0.510	(0.010)	0.446
9. dec	0.723	(0.010)	0.748
10. dec	1.294	(0.010)	1.158
Within-individual mean earnings residual in the U.S. (SIPP):			
1. dec	−1.250	(0.011)	−1.005
2. dec	−0.557	(0.011)	−0.527
3. dec	−0.337	(0.011)	−0.325
4. dec	−0.165	(0.011)	−0.159
5. dec	−0.019	(0.011)	−0.022
6. dec	0.108	(0.011)	0.102
7. dec	0.220	(0.011)	0.227
8. dec	0.356	(0.011)	0.363
9. dec	0.552	(0.011)	0.525
10. dec	0.952	(0.011)	0.822
Duration of last trip to the U.S. | age (MxFLS):			
1. dec of time in U.S.|age	−0.368	(0.028)	−0.615
2. dec of time in U.S.|age	−0.191	(0.032)	−0.354
3. dec of time in U.S.|age	−0.152	(0.030)	−0.311
4. dec of time in U.S.|age	−0.127	(0.034)	−0.302
5. dec of time in U.S.|age	−0.101	(0.030)	−0.281
6. dec of time in U.S.|age	−0.077	(0.031)	−0.271
7. dec of time in U.S.|age	−0.055	(0.031)	−0.263
8. dec of time in U.S.|age	−0.045	(0.029)	−0.242
9. dec of time in U.S.|age	−0.027	(0.031)	0.112
10. dec of time in U.S.|age	1.555	(0.036)	2.599
Duration of current trip to the U.S. | age (SIPP):			
1. dec of time in U.S.|age	−14.885	(0.146)	−12.083
2. dec of time in U.S.|age	−8.583	(0.147)	−5.744
3. dec of time in U.S.|age	−5.536	(0.146)	−3.542
4. dec of time in U.S.|age	−3.310	(0.147)	−1.859
5. dec of time in U.S.|age	−1.348	(0.147)	−0.296
6. dec of time in U.S.|age	0.454	(0.147)	1.169
7. dec of time in U.S.|age	2.341	(0.146)	2.635
8. dec of time in U.S.|age	4.404	(0.147)	4.303
9. dec of time in U.S.|age	7.265	(0.147)	6.211
10. dec of time in U.S.|age	13.838	(0.147)	9.356

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 $\times$ 50 years $\times$ 2 seasons.

Table A10: 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	8.226	(0.033)	8.611
2. dec of last migration duration |age	8.239	(0.037)	8.594
3. dec of last migration duration |age	8.093	(0.037)	8.612
4. dec of last migration duration |age	8.066	(0.042)	8.665
5. dec of last migration duration |age	8.266	(0.036)	8.661
6. dec of last migration duration |age	8.345	(0.035)	8.621
7. dec of last migration duration |age	8.212	(0.036)	8.703
8. dec of last migration duration |age	8.270	(0.035)	8.620
9. dec of last migration duration |age	8.276	(0.036)	8.764
10. dec of last migration duration |age	8.159	(0.045)	9.362
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)	9.515
2. dec of time in U.S.|age	9.556	(0.060)	9.376
3. dec of time in U.S.|age	9.548	(0.054)	9.304
4. dec of time in U.S.|age	9.743	(0.054)	9.368
5. dec of time in U.S.|age	9.711	(0.057)	9.419
6. dec of time in U.S.|age	9.910	(0.058)	9.507
7. dec of time in U.S.|age	9.722	(0.047)	9.562
8. dec of time in U.S.|age	9.986	(0.055)	9.646
9. dec of time in U.S.|age	9.979	(0.070)	9.700
10. dec of time in U.S.|age	9.993	(0.067)	9.821

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

Table A11: Heterogeneity in non-representative samples.

Moment	Data	Standard error	Simulation
Being in the U.S. | age in the MMP:			
1. dec	−0.089	(0.001)	−0.081
2. dec	−0.078	(0.001)	−0.070
3. dec	−0.065	(0.001)	−0.058
4. dec	−0.053	(0.001)	−0.046
5. dec	−0.045	(0.001)	−0.037
6. dec	−0.037	(0.001)	−0.032
7. dec	−0.028	(0.001)	−0.029
8. dec	−0.018	(0.001)	−0.022
9. dec	0.024	(0.001)	−0.014
10. dec	0.395	(0.001)	0.386
Log biannual earnings in Progresa:			
1. dec	6.374	(0.010)	6.338
2. dec	7.186	(0.010)	6.931
3. dec	7.578	(0.009)	7.269
4. dec	7.813	(0.011)	7.489
5. dec	7.975	(0.010)	7.763
6. dec	8.171	(0.009)	8.033
7. dec	8.360	(0.009)	8.313
8. dec	8.412	(0.056)	8.635
9. dec	8.568	(0.010)	8.879
10. dec	9.176	(0.011)	9.536
Regression of log loan take-up during last 6 months (Progresa) on:			
$\mathbb{1}[PROGRESA\ treated]$	0.432	(0.196)	0.384

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 × 2 seasons. 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.

G 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 A12: Structural estimates of family status transition parameters.

Parameter	Point estimate	Standard error
$p_{f+}(\Omega)$:		
ψ_0^{f+}	-1.611	(0.057)
$\psi_{a\leq 30}^{f+}$	0.023	(0.002)
$\psi_{30<a\leq 50}^{f+}$	-0.066	(0.006)
$\psi_{a>50}^{f+}$	0.081	(0.016)
$p_{f-}(\Omega)$:		
ψ_0^{f-}	0.561	(0.046)
$\psi_{a\leq 30}^{f-}$	-0.127	(0.002)
$\psi_{30<a\leq 50}^{f-}$	0.043	(0.003)
$\psi_{a>50}^{f-}$	-0.004	(0.011)

Estimation by indirect inference, based on 40,000 agents × 50 years × 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A13: Structural estimates of legal status transition parameters.

Parameter	Point estimate	Standard error
$p_{d+}(\Omega)$:		
$\psi_0^{\delta+}$	-4.620	(0.118)
$\psi_e^{\delta+}$	1.616	(0.077)
$\psi_{a\leq 30}^{\delta+}$	0.107	(0.006)
$\psi_{30<a\leq 50}^{\delta+}$	0.060	(0.023)
$\psi_{a>50}^{\delta+}$	-0.044	(0.003)
$p_{d-}(\Omega)$:		
$\psi_0^{\delta-}$	-2.276	(0.054)
$\psi_e^{\delta-}$	-0.192	(0.070)
$\psi_{a\leq 30}^{\delta-}$	0.002	(0.003)
$\psi_{30<a\leq 50}^{\delta-}$	-0.049	(0.488)
$\psi_{a>50}^{\delta-}$	-0.075	(0.523)

Estimation by indirect inference, based on 40,000 agents × 50 years × 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A14: Structural estimates of employment transition parameter for Mexico.

Parameter	Point estimate	Standard error
$\lambda_w(\Omega_{it}\|e_{it-1} = nw, l_{it} = MX)$:		
$\psi_0^{w,MX}$	2.034	(0.065)
$\psi_s^{w,MX}$	0.090	(0.009)
$\psi_X^{w,MX}$	-0.107	(0.014)
$\psi_{a\leq 25}^{w,MX}$	-0.106	(0.003)
$\psi_{40<a\leq 55}^{w,MX}$	-0.096	(0.020)
$\psi_{40<a\leq 55}^{w,MX}$	-0.092	(0.007)
$\psi_{a>55}^{w,MX}$	-0.045	(0.212)
$\lambda_{nw}(\Omega_{it}\|e_{it-1} = w, l_{it} = MX)$:		
$\psi_0^{nw,MX}$	-5.530	(0.053)
$\psi_s^{nw,MX}$	-0.015	(0.004)
$\psi_X^{nw,MX}$	-0.056	(0.024)
$\psi_{a\leq 25}^{nw,MX}$	0.094	(0.003)
$\psi_{25<a\leq 40}^{nw,MX}$	0.013	(0.001)
$\psi_{40<a\leq 55}^{nw,MX}$	0.004	(0.006)
$\psi_{a>55}^{nw,MX}$	0.026	(0.027)

Estimation by indirect inference, based on 40,000 agents $\times$ 50 years $\times$ 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A15: Structural estimates of employment transition parameters in the U.S.

Parameter	Point estimate	Standard error
$\lambda_w(\Omega_{it}\|e_{it-1} = nw, l_{it} = US)$:		
$\psi_0^{w,US}$	0.538	(0.072)
$\psi_X^{w,US}$	-0.006	(0.001)
$\psi_\delta^{w,US}$	-0.030	(0.004)
$\psi_s^{w,US}$	-0.438	(0.030)
$\psi_{a\leq 25}^{w,US}$	-0.009	(0.002)
$\psi_{25<a\leq 40}^{w,US}$	-0.073	(0.004)
$\psi_{40<a\leq 55}^{w,US}$	-0.065	(0.007)
$\psi_{a>55}^{w,US}$	-0.093	(0.042)
$\lambda_{nw}(\Omega_{it}\|e_{it-1} = w, l_{it} = US)$:		
$\psi_0^{nw,US}$	-2.148	(0.041)
$\psi_X^{nw,US}$	-0.002	(0.001)
$\psi_\delta^{nw,US}$	-0.024	(0.006)
$\psi_s^{nw,US}$	-0.708	(0.044)
$\psi_{a\leq 25}^{nw,US}$	-0.002	(0.001)
$\psi_{25<a\leq 40}^{nw,US}$	0.002	(0.004)
$\psi_{40<a\leq 55}^{nw,US}$	0.010	(0.003)
$\psi_{a>55}^{nw,US}$	0.189	(0.021)

Estimation by indirect inference, based on 40,000 agents $\times$ 50 years $\times$ 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A16: Structural estimates of earnings function parameters in Mexico.

Parameter	Point estimate	Standard error
α_i^{MX}	5.659	(0.037)
	5.788	(0.028)
	6.424	(0.055)
	6.735	(0.034)
$f^{MX}(a)$:		
$\psi_{a\leq 20}^{y,MX}$	0.101	(0.001)
$\psi_{20<a\leq 25}^{y,MX}$	0.051	(0.002)
$\psi_{25<a\leq 35}^{y,MX}$	0.021	(0.001)
$\psi_{35<a\leq 50}^{y,MX}$	0.009	(0.001)
$\psi_{50<a}^{y,MX}$	0.004	(0.000)
σ_u^{MX}	0.905	(0.022)

Estimation by indirect inference, based on 40,000 agents × 50 years × 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A17: Structural estimates of earnings function parameters in the U.S.

Parameter	Point estimate	Standard error
α_i^{US}	6.589	(0.118)
	7.410	(0.208)
	7.431	(0.177)
	7.494	(0.070)
$f^{US}(a, X)$:		
$\psi_{x\leq 5}^{y,US}$	0.078	(0.003)
$\psi_{5<x\leq 10}^{y,US}$	0.023	(0.002)
$\psi_{x>10}^{y,US}$	0.014	(0.001)
$\psi_{a\leq 20}^{y,US}$	0.051	(0.001)
$\psi_{20<a\leq 25}^{y,US}$	0.028	(0.002)
$\psi_{25<a\leq 35}^{y,US}$	0.023	(0.001)
$\psi_{35<a\leq 50}^{y,US}$	0.007	(0.001)
$\psi_{50<a}^{y,US}$	0.001	(0.006)
σ_u^{US}	1.302	(0.027)

Estimation by indirect inference, based on 40,000 agents × 50 years × 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A18: Structural estimates of preference parameters.

Parameter	Point estimate	Standard error
π_i^{US}	1.290	(0.042)
	0.744	(0.154)
	1.300	(0.026)
	0.604	(0.026)
ϕ_c	0.208	(0.004)
ϕ_A	0.556	(0.176)
$\phi_{f,l\neq l^f}$	0.410	(0.022)
$\phi_{f,l=l^f}$	5.940	(0.253)
σ_0^ε	1.656	(0.029)
σ_a^ε	-0.004	(0.001)

Estimation by indirect inference, based on 40,000 agents $\times$ 50 years $\times$ 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A19: Structural estimates of migration cost parameters ($C(\Omega)$).

Parameter	Point estimate	Standard error
γ_0	5.760	(0.127)
γ_a	0.057	(0.002)
γ_X	-3.212	(0.142)
γ_{undoc}	2.157	(0.211)
γ_f	16.929	(0.510)

Estimation by indirect inference, based on 40,000 agents $\times$ 50 years $\times$ 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A20: 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	-1.749	(0.073)
δ_y	2.835	(0.047)
$\tilde{\alpha}_A$	10.226	(0.227)

Estimation by indirect inference, based on 40,000 agents $\times$ 50 years $\times$ 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

Table A21: 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}	0.403	(0.192)
ω_2^{MMP}	0.092	(0.237)
ω_3^{MMP}	0.213	(0.058)
$\omega_1^{Progresa}$	0.421	(0.433)
$\omega_2^{Progresa}$	0.099	(0.077)
$\omega_3^{Progresa}$	0.196	(0.460)

Estimation by indirect inference, based on 40,000 agents $\times$ 50 years $\times$ 2 seasons; data sources: MxFLS 2002, 2005; SIPP 1996-2007, MMP 1996-2007; and Progresa evaluation data 1998.

H Non-linear Borrowing Constraint

The model in Section 3 assumes a debt limit that is a linear function of expected earnings (subject to the natural borrowing constraint, which binds for older individuals, see Appendix B for details). In this appendix, I examine the importance of this assumption, also in light of available evidence for credit limits. Debt limits are rarely observed. The maybe best direct benchmark for Mexico are the credit card data used by Castellanos et al. (2018). Although theirs is a more urban sample than mine, the reported numbers can be considered a lower bound for borrowing limits within that sample, in that total credit access is in fact higher if individuals have multiple credit cards or other sources of credit. The mean limit reported in Castellanos et al. (2018) is 49,604 pesos (Table 1), or 6,439 PPP adjusted USD. I use this as a maximum amount of debt for all individuals, maintaining the estimated slope parameters δ_0 and δ_y to determine tighter debt limits for low earning households. Table A22 displays the predictions for the main results under this alternative borrowing constraint. As expected, a comparison to Table 3 in the main text reveals that this non-linear credit limit, which reduces credit access at the upper end, matters only for more productive agents. Overall, I find no qualitative and only minor quantitative differences to the estimates in Table 3. The main difference is a lower degree of borrowing for migration, and a higher amount of savings accumulated abroad. Changes in migration duration and the number of migrations are small.

Table A22: Alternative model: 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	6.03	5.21	2.52	2.43
(b) Number of migrations	1.68	1.72	1.96	2.00
(c) Share with fam. in U.S.	0.35	0.37	0.53	0.52
(d) Loan taken per trip	1073.00	1378.45	1520.58	1528.21
(e) Saving abroad per trip*	4479.15	4307.23	6622.57	6269.47

Note.— Counterfactual outcomes as predicted by an alternative model with an upper limit to borrowing of 6,439 PPP adjusted USD. The table is the counterpart to Table 3 in the main text and shows changes for 10% higher origin country earnings, separately for individuals with below and above median productivity. Simulation based on 40,000 agents.

* Accumulated savings abroad conditional on migrants returning.